Essays on Fisheries Management: Instrument Choice and the Design of Marine Reserves under Uncertainty

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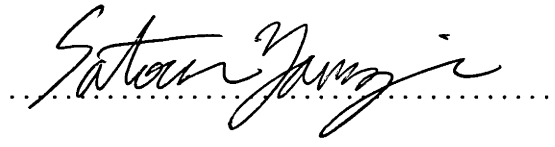
Declaration

Except where otherwise acknowledged, the material presented in this thesis is, to the best of my knowledge and belief, original and has not been submitted for a degree at any other university. Part of this thesis research is based on joint research with my supervisors, Professor Tom Kompas and Professor R. Quentin Grafton, including the material in Chapter 2, which is published as Yamazaki, S., Kompas, T. and Grafton, R.Q., 2009. 'Output versus input controls under uncertainty: the case of a fishery', *Natural Resource Modeling*, 22: 212-236.



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Abstract

The primary contribution of this thesis is to develop a series of bioeconomic models and a decision framework to assess the outcomes of fisheries management and provide policy recommendations. Using estimated parameters from different fisheries worldwide, biological, economic and social outcomes under different management scenarios were simulated and compared.

The thesis consists of three main essays focusing on issues in fisheries instrument choice and the design of marine reserves. The first essay assesses and compares the economic and biological outcomes of different fisheries regulations under a stochastic environment. One important issue in fisheries management is whether to control the inputs of resource users or the actual level of harvest when there are uncertainties in stock-recruitment and harvest-effort relationships. Using a dynamic programming model with parameter estimates from an actual fishery, this essay investigates to what extent tradeoffs can be made between the total catch level and the risk of overfishing, and also to what extent uncertainties in both the stock-recruitment and harvest-effort relationships affect the choice of total output versus total input controls.

The second and third essays address the issues of marine reserves. A number of previous studies have suggested that, with appropriate fisher and market incentives, the establishment of reserves will increase biological, economic and social benefits from fisheries. However, whether the use of reserves has ex-

pected and desirable outcomes strictly depends on the marine reserve design, including the size, location, as well as duration of closure for fishing and connectivity between reserve and harvested populations. The second essay of the thesis evaluates the impact of rotating a reserve over time. Using a stochastic bioeconomic model, we simulate the economic and biological benefits and compare the outcomes between different management scenarios. In this essay, we also model the non-market value of marine reserves and analyse how the optimal rotation rule changes in different forms of the non-market value function. The third essay discusses the connectivity and network structure of marine reserves. In this essay we develop a spatial bioeconomic model and show how the connectivity between adjacent sites and the spatial heterogeneity in economic and biological variables affect the spillover effect between neighbouring sites.

Contents

Chapter 1

Introduction

Overview of the thesis

Many modern fisheries are in trouble worldwide and facing various issues and challenges, such as degradation of the ecosystem, depletion in fish stocks as well as increasing fishing capacity and decreasing economic profit (Pauly 1998; World Bank 2004; Worm et al. 2006). The primary causes of the problems are complex and inter-related. They include inappropriate incentives, high demand for limited resources, poverty and lack of alternatives, complexity and lack of knowledge, ineffective systems of governance, and the interactions of the fisheries sector with other sectors and the environment (FAO 2004). The Food and Agricultural Organization (FAO) reported that about 25 per cent of the fish stocks monitored by FAO are either overfished, depleted, or recovering from depletion, while about half of the stocks are fully exploited and there is no room for expansion (FAO 2007).

Maintaining sustainable fisheries and restoring ecosystems in the long-run will guarantee a stable food supply, secure income sources as well as job opportu-

nities and enhance amenity values of the coastal environment. Fisheries management is a complex system interacting with biological, economic and social behaviours. It is challenging but both public and private benefits from fisheries will be improved through institutional changes, including learning from the experience of successful fisheries, applying insights from science and managing market incentives with appropriate individual harvesting rights (World Bank 2004; Grafton et al. 2006a; Hilborn 2007; Wilen 2006; Sanchirico & Wilen 2007; Costello et al. 2008; Grafton et al. 2008).

The thesis focuses on issues in fisheries instrument choice and the design of marine reserves. The primary contribution of the thesis is to develop a series of bioeconomic models and a decision framework to assess outcomes of fisheries management and provide policy recommendations.

The analytical method employed in this thesis research is a stochastic dynamic optimisation approach. The developed models are solved using numerical methods. One advantage of using this method is that it allows us to specify the optimal time paths of the stochastic harvest, biomass and economic profit, in which the dynamic maximum economic yield (MEY) is achieved. At MEY, the discounted economic profit from fishing is maximised. Specifying sensible MEY levels is a fundamental issue in fisheries management, since not only the economic profit of a fishery is maximised but also the biomass at MEY could be greater than that at maximum sustainable yield (MSY) where the population growth is maximised (Grafton et al. 2007). In this thesis, we compare the MEY levels as well as economic and biological benefits between different management strategies.

By contrast, a disadvantage of numerical methods is that the functional forms and parameters values have to be chosen and well-specified. Another potential problem with numerical methods is that the solutions are approximate. While

in this thesis an extensive sensitivity analysis is undertaken for each study, more general qualitative structure of the results can be derived by analytical methods (Judd 1998). However, due to the complexity of the problems, it is often not possible to obtain the analytical solutions and numerical methods have to be employed.

Structure of the thesis

Following the introduction, this thesis is comprised of three main essays, which are based on joint research with Professor Tom Kompas and Professor R. Quentin Grafton. The first essay (Chapter 2) is based on a published article in *Natural Resource Modeling* (doi: 10.1111/j.1939-7445.2008.00034.x). An important issue in natural resource management is whether to control the total effort or actual amount of resource exploitation. In this essay, we compare the management outcomes with a total allowable catch (TAC) and a total allowable effort (TAE) in a fishery under uncertainty. Using a dynamic programming model with multiple uncertainties and estimated growth, harvest and effort functions from one of the world's largest fisheries, the relative economic and biological benefits of a TAC and TAE are compared and contrasted in a stochastic environment. This approach provides a decision and modeling framework to compare instruments and achieve desired management goals. A key finding of this essay is that neither instrument is always preferred in a world of uncertainty. Instrument choice is determined by the regulator's risk aversion and weighting in terms of expected net profits and biomass, and the trade-offs in terms of expected values and variance.

In the second and third essays, we investigate the design of marine reserves. The creation of marine reserves has received increased attention by both fish-

eries managers and scientists to mitigate failures in traditional fisheries management. In the second essay (Chapter 3), we develop a stochastic bioeconomic model to analyse a fisheries management strategy, marine reserves switching, incorporating the non-market value of reserves. In the switching strategy a non-fishing area is rotated from one site to another over time according to economic criteria. The simulation results show that, even if there are weak linkages between adjacent sites, the switching strategy is likely to maintain a high catch level as well as fish abundance. We also show that fixing a non-fishing area at one site significantly decreases the total harvest if the linkage between adjacent sites is weak. With respect to the non-market value of reserves, we illustrate how the optimal switching rule changes with different characteristics of the non-market value.

The economic benefit of establishing a reserve depends strictly on fish dispersal between adjacent sites. The use of reserves is economically optimal if and only if the dispersal benefit from the reserve to harvested populations is greater than the cost of reductions in fishing waters from closing a fishing ground. In the third essay (Chapter 4), we examine the connectivity and network structure of marine reserves. The biological system is typically heterogeneous between different areas. Considering spatial characteristics in the management area makes the decision process more complex. In this essay we develop a spatial bioeconomic model, which incorporates a simple network structure of marine reserves. We then numerically solve and simulate the model using a feedback approximation method. A key finding is that weak connectivity between the reserve and harvested populations maintains the reserve population better than strong connectivity. In contrast, the strong connectivity averages the population density between protected and fishing areas faster and this results in greater economic returns. Another finding of this essay is that, with appropriate harvest limits, the dispersal benefit from reserves to adjacent fisheries is

enhanced under a heterogeneous environment. This result suggests that, especially in a heterogeneous environment, a spatially explicit control of resource use outweighs a non-spatial one.

Chapter 2

Output versus input controls under uncertainty: The case of a fishery

Introduction

A fundamental issue when managing common-pool resources is whether to control the inputs or efforts of resource users or their actual level of use or harvest. In a deterministic world with perfect information and enforcement, both approaches generate identical outcomes. However, in a world of uncertainty the two methods of regulation differ in their effects just as prices and quantities differ in their impacts (Weitzman 1974; Jensen & Vestergaard 2003).[1]

We address the problem of how to manage renewable resources under uncertainty by comparing two high-order methods of regulation: a total allowable catch (TAC) that limits the total harvest and a total allowable effort (TAE) that regulates the total level of effort expended by harvesters. Whether a TAC or TAE is preferred depends on the relative costs in monitoring[2] and enforcement, the ability of fishers to substitute to non-ITQ species or unregulated fishing inputs, the uncertainty between fishing effort and harvest, and

the uncertainty between the fish stock and the level of recruitment or growth in the fishery. In this paper, we confine our analysis to how the uncertainty affects the relative efficiency between TAC and TAE controls. Focusing on uncertainty, we show what circumstances favour TAC versus TAE controls.

A TAC provides direct control over harvesting mortality but only indirectly controls the effort expended by harvesters, whereas a TAE directly limits effort and only indirectly limits the amount harvested. In the case of TAE control, fishers may be able to substitute to unregulated inputs to offset the limits imposed by managers (Dupont 1991) but ineffective monitoring and enforcement will limit the ability of a TAC to control the harvests of fishers. Both approaches can be established as market-based instruments. In the case of total harvest (under TAC control) rights can be allocated as individual transferable harvesting quotas, whereas for total fishing effort (under TAE control), rights can be allocated in the form of individual transferable effort quotas.

The existing literature shows that the more uncertain is the relationship between current stocks and future recruitment, the more difficult it becomes to effectively set a TAC control. Similarly, the less predictable is the relationship between fishing inputs and level of catch, the less effective is a TAE control in obtaining the desired level of harvest (Danielsson 2002; Kompas et al. 2008). Although these are important insights, there remain several important questions to be answered when comparing the two instruments. For instance, to what extent can trade-offs be made between the total catch level and the risk of overfishing? To what extent do uncertainties in both the stock recruitment and harvest–effort relationships affect the choice of TAC versus TAE control? To what extent do comparisons of the instruments using cumulative density functions rather than expected values provide added insights about regulatory choice under uncertainty?[3] To address these knowledge gaps, we employ a dy-

namic optimisation model under multiple uncertainties with estimated growth, harvest and effort functions to simulate the economic and biological benefits under TAC and TAE controls.

The paper is organized as follows. In Section 2.2, we describe the results from previous modelling and describe our own "benchmark" bioeconomic model under multiple uncertainties. Section 2.3 describes the simulation method and estimates the model parameters using annual time series data from the skipjack fishery in the Western and Central Pacific Ocean. Numerical results, the trade-offs between TAC and TAE controls and the effects of uncertainty on the relative payoffs are explored in Section 2.4. A discussion of the results is given in Section 2.5 and Section 2.6 provides concluding remarks.

Modelling TAC and TAE controls

A small but important literature has developed over the relative merits of TAC and TAE controls in fisheries. Using a one-period model with uncertainty in terms of the current biomass, Hannesson and Steinshamn (1991) showed that the actual difference between a constant catch quota and constant effort is very small and the most important determinant of the relative profitability between them is the size of the stock effect in the harvest function. They also found that, as fishing cost decreases, the constant effort strategy becomes less profitable. Quiggin (1992) generalised the Hannesson and Steinshamn model and showed that there is a constant effort rule that generates a higher economic return for every constant catch rule. Danielsson (2002) subsequently developed a dynamic model to compare the relative efficiency of TAC and TAE controls and also added an additional level of uncertainty. He found that if the price elasticity of demand is low and the relative variability in the growth of the

stock to the catch per unit of effort is low, then a TAC is preferred to a TAE. However, TAE control is superior if the price elasticity of demand is high and there is high variability in the biomass relative to the catch per unit of effort. In an extension of Danielsson's work, Kompas et al. (2008) developed a dynamic model utilizing data from the Northern Tiger Prawn fishery of Australia. They find that given the estimated variability in the stock–recruitment relationship and catch per unit of effort that the use of a TAC is preferred in that fishery because both expected profits and the stock are higher at the steady state with a TAC and because the variation in the stock is always less with the TAC than TAE.[4]

We develop a bioeconomic model based on the models in Hannesson and Steinshamn (1991) and Danielsson (2002). This permits us to compare and contrast our results to previous studies. To compare TAC and TAE controls we specify a monotonic harvest-effort relationship represented by the general form given in (2.1)

$$h_t = f(E_t,\ x_t) = qE_t^{\gamma 1}x_t^{\gamma 2} \tag{2.1}$$

where h_t is the harvest level at time t. The function f is the deterministic harvest function with the effort level E_t, biomass level x_t and a constant catchability coefficient q at time t. The parameters $\gamma 1$ and $\gamma 2$ determine the importance of effort and stock levels in the harvest function. We define $\gamma 2$ as a stock effect. Given the assumption of $\partial h_t/\partial E_t > 0$, the effort function, or the inverse of (2.1) is:

$$\begin{aligned} E_t &= f^{-1}(h_t,\ x_t) \\ &= g(h_t,\ x_t) \\ &= \left(\frac{h_t}{qx_t^{\gamma 2}}\right)^{1/\gamma 1} \end{aligned} \tag{2.2}$$

Uncertainty is introduced by including random variables in the harvest and effort functions, respectively, i.e.,

$$h_t = F(E_t,\ x_t,\ z_t^h) = z_t^h q E_t^{\gamma 1} x_t^{\gamma 2} \tag{2.3}$$

and

$$E_t = G(h_t,\ x_t\ z_t^e) = z_t^e \left(\frac{h_t}{q x_t^{\gamma 2}}\right)^{1/\gamma 1} \tag{2.4}$$

where F and G are respectively the harvest and effort functions with the random variables z_t^h and z_t^e that can be interpreted as 'policy implementation errors', respectively in the TAE and TAC controls. In other words, z_t^h is realized only when the TAE control is implemented, and z_t^e is realized only when the TAC control is used as an instrument.

We also specify a stock density dependent stochastic growth function as follows:

$$x_{t+1} - x_t = z_t^g r x_t \left(1 - \frac{x_t}{K}\right)^{\alpha} - h_t \tag{2.5}$$

where r is the intrinsic growth rate, K is the carrying capacity and α represents the skewness of the growth function. The change in the biomass over a period is the difference between the harvest level and the random growth in the stock. The random variable z_t^g represents unknown variability in the growth in the biomass.

Objective function and constraints

For both TAC and TAE controls, we assume the regulator wishes to maximize the discounted net profits from fishing over an infinite time horizon and that the choice of which instrument to use cannot be changed. This assumption is not restrictive to our objective of comparing the relative biological and

economic payoffs between the two fisheries instruments under various forms of uncertainty. Indeed, the two instruments can be more explicitly compared if the choice of instrument is not switched over time because our simulations will depend on the performance of only each instrument at a time.

The regulator's optimization problem is to maximize the objective function (2.6) subject to constraints (2.7).

$$\max_{E_t \text{ or } h_t} \mathbb{E} \sum_{t=0}^{\infty} \beta^t \pi_t \tag{2.6}$$

subject to

$$\begin{aligned} x_{t+1} - x_t &= z_t^g r x_t \left(1 - \frac{x_t}{K}\right)^{\alpha} - h_t \\ x_0 &= x(0) \\ z_0^i &= z^i(0), \ i \in \{h, e, g\} \end{aligned} \tag{2.7}$$

where $\mathbb{E}$ is the mathematical expectation operator and β is the time discount factor. We define π_t as the net profit at time t and $\pi_t = p(h_t)h_t - cE_t$, where $p(h_t)$ is the inverse demand function and c is cost per unit of effort. In a TAC controlled fishery the regulator seeks to set an optimal harvest quota to maximize discounted net profits while under a TAE control the regulator sets the optimal effort quota. Our model disregards costs connected with monitoring and enforcement for the two different instruments and the ability of fishers to substitute to non-targeted species or unregulated inputs. As in Danielsson (2002), this allows us to focus on the effects of uncertainties in the stock-recruitment relationship and the harvest-effort relationship on the relative efficiency of TAC and TAE controls.

The inverse demand function is specified as $p(h_t) = \bar{p}h_t^{-1/\delta}$, where δ is the price elasticity of the demand and $\bar{p}$ is a parameter. This specification is commonly used in bioeconomic modeling (Clark 1990) and can encompass various forms of the demand function depending on the parameter δ. For example, as $\delta \to \infty$, $p(h_t) \to \bar{p}$ and the price converges to a constant.

Our model implicitly indicates the importance of including both the population dynamics and different forms of uncertainty when the two fisheries instruments are compared. Given strict convexity of the harvest and concavity of the effort functions it follows from Jensen's inequality (Jehle & Reny 2001) that with a given stock level $x = x^*$, $F(E_t,\ x_t^*,\ \mathbb{E}\left[z_t^h\right]) < \mathbb{E}\left[F\left(E_t,\ x_t^*,\ z_t^h\right)\right]$ and $\mathbb{E}G\left(E_t,\ x_t^*,\ z_t^e\right) < G\left(h_t,\ x_t^*,\ \mathbb{E}\left[z_t^e\right]\right)$.[5] This result implies that, with a fixed stock level, harvest control will yield a smaller catch and also a smaller effort level on average under the stochastic environment. However, the inequalities do not always hold because of the random variable that varies the biomass over time. For example, assume that F is increasing and G is decreasing function of the biomass and if , $x_t^* > \tilde{x}_t$ then $F(E_t,\ x_t^*,\ \mathbb{E}\left[z_t^h\right]) \geq \mathbb{E}\left[F\left(E_t,\ \tilde{x}_t,\ z_t^h\right)\right]$ and $\mathbb{E}G\left(E_t,\ \tilde{x}_t\ z_t^e\right) \geq G\left(h_t,\ x_t^*,\ \mathbb{E}\left[z_t^e\right]\right)$ can hold, respectively. Consequently a model that accounts for uncertainty in the growth function and the population dynamics over time will yield different results than a one period model.

The recursive form of the problem for each control variable is as follows. For TAE control it takes the following form:

$$V^e(x_t) = \max_{E_t}\left(\mathbb{E}\left[p \cdot z_t^h q E_t^{\gamma 1} x_t^{\gamma 2}\right] - cE_t + \beta \mathbb{E}V^e\left(x_{t+1},\ z_{t+1}^g\right)\right) \tag{2.8}$$

and for TAC control it is:

$$V^h(x_t) = \max_{h_t}\left(ph_t - \mathbb{E}\left[c \cdot z_t^e\left(\frac{h_t}{q x_t^{\gamma 2}}\right)^{1/\gamma 1}\right] + \beta \mathbb{E}V^h\left(x_{t+1},\ z_{t+1}^g\right)\right) \tag{2.9}$$

where the left hand side of the both equations (2.8) and (2.9) represents the value function, which is the maximum attainable objective function at time t. The right hand side of the equations has two parts. The first two terms are the expected net profit at time t ($\mathbb{E}[\pi_t]$) and the last term $\beta \mathbb{E} V^i(x_{t+1},\ z^g_{t+1})$, $i \in \{e, h\}$, is the discounted expected value function at time $t+1$. The solution to the optimization problems in (2.8) and (2.9) yields, respectively, the optimal effort level and harvest level as a function of the stock level. As a result of the random variables the optimal levels of effort and harvest may not equal their actual levels.

Western and Central Pacific Skipjack Fishery

The problem of instrument choice is applied to the Western and Central Pacific skipjack fishery.[6] It is one of the world's largest fisheries in terms of total harvest and generates landings of approximately 1.2 million metric tons per year (Langley et al. 2005). The fish are harvested primarily by purse seine vessels that are highly capital intensive, although some skipjack is also caught by pole-and-line vessels. Overall, the fishery is characterized as a high volume but low value fishery per unit harvested (Barclay & Cartwright 2007). Although concerns have been raised about the sustainability of other tuna species (in particular bigeye), the biomass of skipjack still remains above its maximum sustained yield (Langley et al. 2005).

The management of the fishery is overseen by the Western and Central Pacific Fisheries Commission (WCPFC) — a regional fisheries management organization (Parris & Grafton 2006). The WCPFC acts on behalf of its member nations, which include coastal states and distant water fishing nations, and sets rules for its members that apply to both EEZ and the high-seas zones

of the fishery. Its decisions are binding on member states 60 days after their adoption. Decisions are, in the first instance, to be made by consensus, and if this is not possible and only after all efforts to reach a decision by consensus have been exhausted, decisions can be made by a three-fourths majority of members.

To address concerns over higher than desired levels of fishing mortality for yellowfin, and especially bigeye tuna, members of the WCPFC have agreed to implement a type of TAE in the form of a vessel day scheme (VDS) for these tuna species that will restrict the number of days fished to an average over the 2001–2004 period. Although fishing effort for skipjack tuna is not directly controlled by the VDS, the scheme will also regulate the skipjack fishery as bigeye and yellowfin are important bycatches.

We employ Non-Linear Least Squares (NLS) estimation techniques to estimate the economic and biological parameters for our model by using annual time series data (i.e., catch and effort levels and a stock assessment estimate of biomass from 1972 to 2002) from the skipjack tuna purse seine fishery. The effort level is measured by days at sea fishing and searching for fish. Details of the estimation are provided in Table 2.1 for both the growth function and the harvest function. The intrinsic growth rate (r) and the parameter in the growth function (α) are estimated as $r = 1.31$ and $\alpha = 0.89$. The goodness of the fit for the growth function is 0.58 and both parameters are statistically significant at 5 per cent level. The parameters in the harvest function are estimated as $\ln(q) = -1.93$, $\gamma 1 = 1.37$ and $\gamma 2 = 0.27$. The goodness of the fit for the harvest function is 0.91. The catchability coefficient (q) and the parameter ($\gamma 1$) are statistically significant at 5 percent level, but the stock effect ($\gamma 2$) is not significant. Hence, we first set $\gamma 2 = 0$ to obtain base case results and then apply $\gamma 2 = 0.27$ for the sensitivity analysis of the stock effect

Table 2.1 **Estimation results of the growth function and the harvest function**

Growth function		
Parameter	**Coefficient**	**t-statistics**
r	1.31	8.50
		(0.154)
α	0.89	2.25
		(0.396)
Number of observation	30	
R-squared	0.58	
Harvest function		
Parameter	**Coefficient**	**t-statistics**
$\ln(q)$	-1.93	-1.97
		(0.978)
$\gamma 1$	1.37	-16.71
		(0.082)
$\gamma 2$	0.27	-1.34
		(0.202)
Number of observation	31	
R-squared	0.91	
P-value (F-statistics)	0.000	

Note: Numbers in parentheses are standard errors

in the harvest function. For ease of exposition the carrying capacity (K) is normalized to unity such that the biomass (x) represents density rather than actual weight of fish.

The price elasticity of demand and the cost parameter are obtained from Bertignac et al. (2000). The price elasticity is set at $\delta = 1.55$ and the cost parameter is set at $c = 14.5$. Due to the lack of the adequate price data, the parameter in the inverse demand function ($\bar{p}$) is initially set at 50 to ensure the existence of a unique steady state and the sensitivity analysis is undertaken. The base-case results are derived with the statistically significant estimated parameters and alternative parameters are applied for a sensitivity analysis. This allows us to investigate how the relative efficiencies between the two instruments change depending on the parameter values.

The stochastic factors z^h, z^e and z^g are specified as $z^i = 1 + (2u - 1)\epsilon^i$,

$i \in \{h,\ e,\ g\}$, where u is uniformly discretised with 10 grids (Sethi et al. 2005). The term ϵ determines the size of variations in the harvest and effort functions and growth function. It lies between 0 and 1, indicating from 0 percent to 100 percent variations. It is important to note that this specification of the uncertainty implies that resource managers do not have exact information of the variation in the fish growth function and harvest and effort functions, but they do know about the source of uncertainty (which variables contain unpredictable variations) and their distributions (how large the variations would be).

Model results

To solve the recursive problems in (2.8) and (2.9) numerically, the value function iteration is utilized with evenly discretised 300 state space grids.[7] This is implemented using a numerical method in Matlab[8] and two expectation terms are calculated. One is the expectation of the net returns for the 'implementation uncertainty' (uncertainty in the harvest and effort functions) for all possible combinations of the state variables in the current (x_t) and next period (x_{t+1}). The other is the expected value of the value function for the 'growth uncertainty' (uncertainty in the growth function). At each iteration (updated from the previous iteration), the optimal policy rule function ($\Phi : \mathbb{R}_+ \times \mathbb{R}_{++} \rightarrow \mathbb{R}_t$) is determined to maximize the objective function for each of the current states and the realization of the growth uncertainty ($x_{t+1} = \Phi(x_t,\ z_t^g)$). The value function is iterated until a convergence criterion is satisfied ($\| V^{l+1} - V^l \| < e^{-10}$ where the superscript l represents the number of iteration).

Using an optimal control rule derived from the converged value function (V^*)

Table 2.2 **Biomass, net profits, harvest and effort at the steady state under a deterministic environment**

	Biomass	Net profit	Harvest	Effort
TAC	0.946	11.040	0.092	0.720
TAE	0.946	11.040	0.092	0.720

Note: The carrying capacity is normalised and each variable has the following domains: $0 \leq x \leq 1$, $0 \leq \pi \leq 11.040$, $0 \leq h \leq 1$ and $0 \leq E \leq 4.094$.

with a given initial stock and tracking the Markov transitions in z^h, z^e and z^g, 50,000 sets of time series are simulated for the optimal policy rule, stock level and economic returns for the TAC and TAE. These calculated values are restricted to $0 \leq h_t^* \leq K$, $0 \leq E_t^*$, $0 \leq x_t^* \leq K$ and $0 \leq \pi_t^*$, which imply that these variables are non-negative and the harvest and biomass cannot exceed the carrying capacity. Due to the normalization of carrying capacity (K), the units of the biomass and harvest are defined as densities and the units of the effort and net profit become indexes. Consequently, the domain for the biomass and harvest is from 0 to 1 for both TAC and TAE controls, but the domains for the effort and net profit vary, depending on the instrument choice, the values of the parameters and the relative size of the uncertainty in the growth and harvest-effort functions.

The steady state values of the biomass, net profits, harvest and effort levels under the deterministic case, where $\epsilon^h = 0$, $\epsilon^e = 0$ and $\epsilon^g = 0$ are presented in Table 2.2.[9] Without any stochasticity in the growth and harvest-effort functions, both the optimal net profits and fish stock level are identical for the TAC and TAE. This is because under perfect information, enforcement and without any implementation error, the fishery manager can optimally control the harvest and effort level to maximize the discounted net profits by using either instrument.

TAC versus TAE control

In order to determine the superiority among the two fisheries instruments in a

stochastic environment, a reference point must be assigned.[10] This is because the superiority between the fisheries instruments may change, depending on what performance measures are used to assess (Francis and Shotton 1997). Kompas et al. (2008) use expected values to compare TAC and TAE controls. A potential problem with their approach, however, is that a single value of the expected value of the outcomes (net profits and biomass) does not provide a perfectly general reference point to compare the two instruments. In other words, expected values only provide a single reference point and analysing the distribution of possible outcomes would provide useful insights. In addition, through simulations we found that there is a relatively small difference between the expected values derived from the two control variables at given parameter values.[11] We overcome this deficiency by constructing a cumulative density function (CDF) of the outcomes averaged over 50 periods to capture the difference in the two instruments.

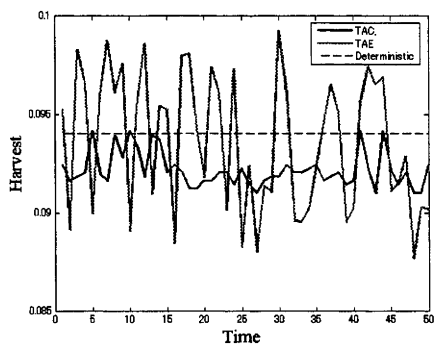
The CDF describes the probability distribution of all possible outcomes and for each instrument is drawn from the 50,000 simulations. In each CDF figure, the point where CDF = 0.5 represents the median of the 50,000 simulations. The intersection of the two functions derived from each fisheries instrument represents the point at which the outcomes from the two instruments are identical. If the intersection is either below or above the point where CDF = 0.5 then one of the instruments is superior to the other in the sense that one instrument's outcome is greater than the other's with a higher probability.

Optimal time path

Figure 2.1 presents the sample optimal time path for the harvest and effort levels under two different scenarios.[12] In the first case, the relative uncertainty in the growth function is small relative to the harvest–effort function ($\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$), but in the second case there is much more uncertainty

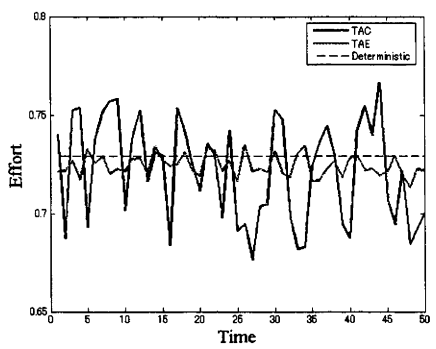
Figure 2.1 **Optimal sample time paths for harvest and fishing effort in the stochastic environment**

2.1.1 Optimal sample time path for harvest ($\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$)



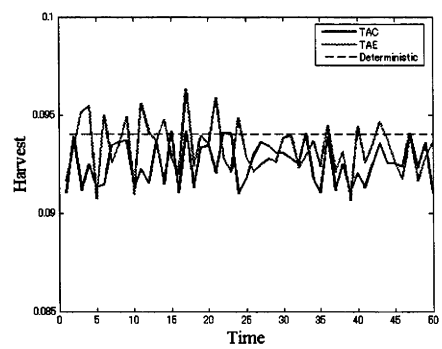
(domain: $0 \leq h \leq 1$)

2.1.2 Optimal sample time path for effort ($\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$)



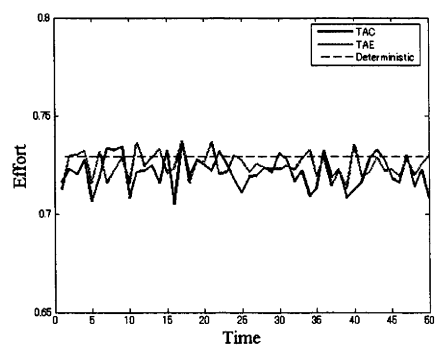
(domain: $\begin{matrix} 0 \leq E^{TAC} \leq 4.30 \\ 0 \leq E^{TAE} \leq 4.25 \end{matrix}$)

2.1.3 Optimal sample time path for harvest ($\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$)



(domain: $0 \leq h \leq 1$)

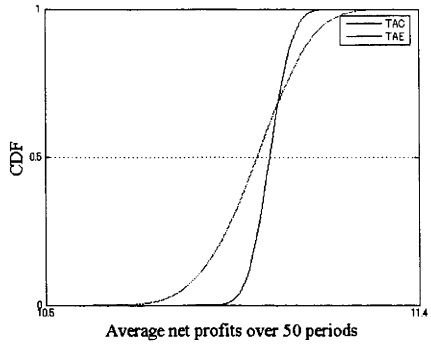
2.1.4 Optimal sample time path for effort ($\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$)



(domain: $\begin{matrix} 0 \leq E^{TAC} \leq 4.13 \\ 0 \leq E^{TAE} \leq 4.12 \end{matrix}$)

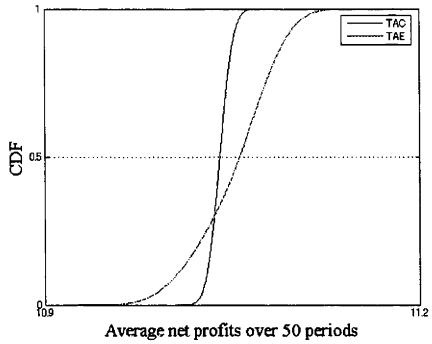
Figure 2.2 **CDF of average net profit with different size of uncertainties** ($\gamma 2 = 0$)

2.2.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$



(domain: $\begin{matrix} 0 \leq \pi^{TAC} \leq 11.59 \\ 0 \leq \pi^{TAE} \leq 11.42 \end{matrix}$)

2.2.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$



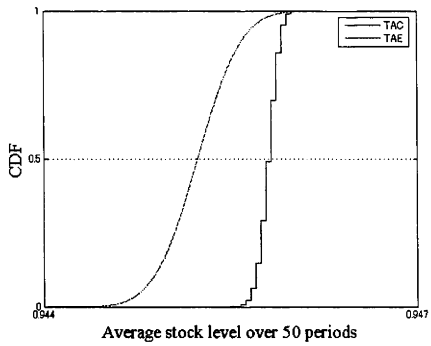
(domain: $\begin{matrix} 0 \leq \pi^{TAC} \leq 11.15 \\ 0 \leq \pi^{TAE} \leq 11.12 \end{matrix}$)

in the growth function relative to the harvest–effort function ($\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$).[13] The dotted line is the optimal time path under the deterministic environment with no uncertainty ($\epsilon^g = 0$, $\epsilon^h = 0$ and $\epsilon^e = 0$). When the uncertainty in the harvest and effort functions is relatively large, the harvest level with the TAE has a greater variation than that with the TAC, but the variation in the level of effort is smaller than with the TAC. This is because the TAC directly controls the harvest level, whereas the harvest in the TAE is indirectly determined by setting the optimal effort quota. Figure 2.1 also shows that the variations in the harvest and effort levels are greater when the uncertainty in the harvest–effort function is relatively large. Moreover, the time paths under the stochastic environment, especially the harvest with the TAC and the effort level with the TAE, tend to be lower than those under the deterministic case. This is because with a stochastic environment and a strictly concave profit function, the harvest and effort quotas are set to a lower level to avoid overfishing.

Figures 2.2.1 and 2.2.2 illustrate how the relative economic payoffs between the two instruments changes according to the relative size of the uncertainty. If the uncertainty in the growth function is small (Figure 2.2.1: $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$), the relative economic payoff favours the TAC control. This

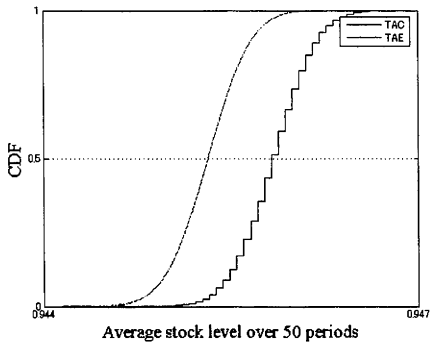
Figure 2.3 **CDF of average biomass with different size of uncertainties** ($\gamma 2 = 0$)

2.3.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$



(domain $0 \leq x \leq 1$)

2.3.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$



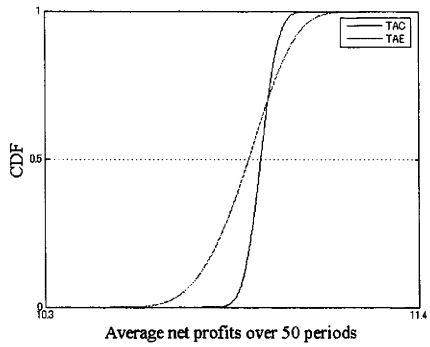
(domain $0 \leq x \leq 1$)

is shown in Figure 2.2.1 by the intersection of the TAC and TAE CDFs at a point greater than 0.5. By contrast, if the uncertainty in growth function is large (Figure 2.2.2: $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$), the TAE has a higher payoff than the TAC with a higher probability as shown by the intersection of the CDFs at a point less than 0.5. The greater is the variation in the harvest–effort function then larger is the variation in the harvest level with a TAE control that, in turn, contributes to over- or underfishing. On the other hand, the greater is the variation in the biomass growth function, the larger is the regulator's error in predicting the following period's stock level, such that TAC control is set at either at too high or too low a level thereby reducing its efficacy as a policy instrument.

Figures 2.3.1 and 2.3.2 provide a comparison between TAC and TAE controls in terms of the average biomass.[14] In both cases, a TAC control delivers a higher average biomass. The larger the variation in the biomass growth function relative to the variation in the harvest– effort function, the larger is the average biomass associated with TAC control compared to TAE control. This is because with a relatively high realization in the biomass a TAC control increases the likelihood of harvesting less than what is optimal relative to a TAE control. As a result, the TAC maintains on average a greater biomass than

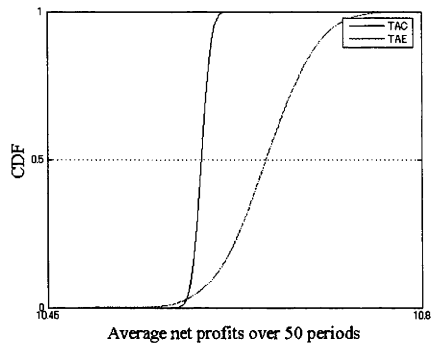
Figure 2.4 **CDF of average net profit with different size of uncertainties** ($\gamma 2 = 0.27$)

2.4.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$



(domain: $\begin{matrix} 0 \leq \pi^{TAC} \leq 11.59 \\ 0 \leq \pi^{TAE} \leq 11.42 \end{matrix}$)

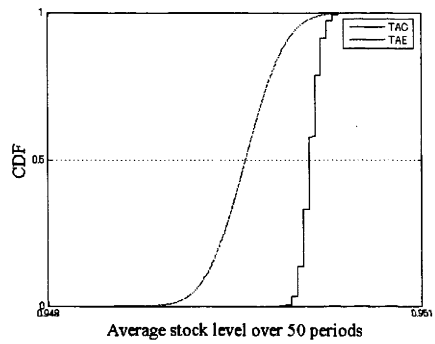
2.4.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$



(domain: $\begin{matrix} 0 \leq \pi^{TAC} \leq 11.15 \\ 0 \leq \pi^{TAE} \leq 11.12 \end{matrix}$)

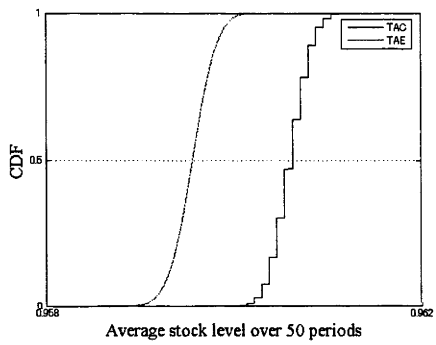
Figure 2.5 **CDF of average biomass with different size of uncertainties** ($\gamma 2 = 0.27$)

2.5.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$



(domain $0 \leq x \leq 1$)

2.5.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$



(domain $0 \leq x \leq 1$)

TAE control. This result is consistent with that in Figure 2.1. Because of the curvature of the profit function, the optimal time path for the harvest in the TAC control is, on average, lower than that in the TAE control.

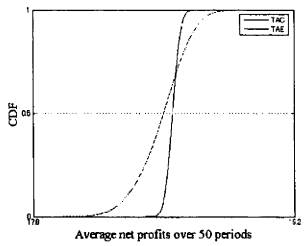
Sensitivity analysis: stock effect

The estimated value of the stock or biomass dependency parameter, $\gamma 2$, in the harvest function was not significantly different from zero at the 5 per cent level of significance. However, the 'stock effect' has been shown to be important in some fisheries so we assess the sensitivity of the results to changes in this parameter.[15] Figures 2.4 and 2.5 show how the results change when there is a weak link ($\gamma 2 = 0.27$) between the harvest and the biomass. Although there is

Figure 2.6 **CDF of average net profit with different price elasticities** ($\gamma 2 = 0$)

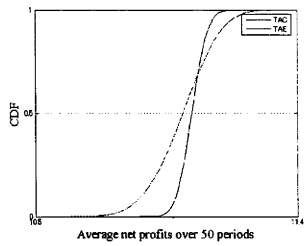
2.6.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$

$\delta = 1.3$



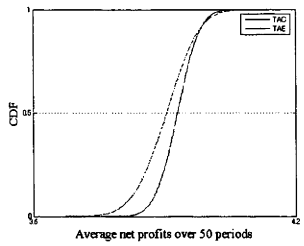
(domain: $0 \leq \pi^{TAC} \leq 18.99$, $0 \leq \pi^{TAE} \leq 18.85$)

$\delta = 1.55$



(domain: $0 \leq \pi^{TAC} \leq 11.59$, $0 \leq \pi^{TAE} \leq 11.42$)

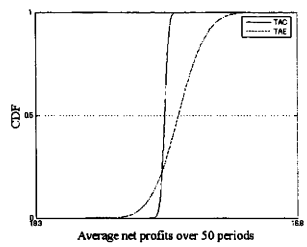
$\delta = 2.1$



(domain: $0 \leq \pi^{TAC} \leq 4.47$, $0 \leq \pi^{TAE} \leq 4.30$)

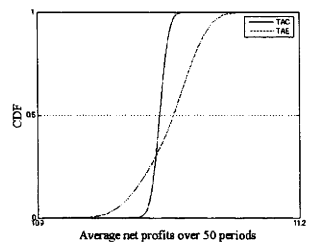
2.6.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$

$\delta = 1.3$



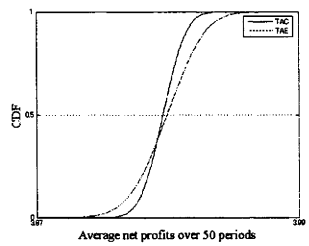
(domain: $0 \leq \pi^{TAC} \leq 18.63$, $0 \leq \pi^{TAE} \leq 18.61$)

$\delta = 1.55$



(domain: $0 \leq \pi^{TAC} \leq 11.15$, $0 \leq \pi^{TAE} \leq 11.12$)

$\delta = 2.1$



(domain: $0 \leq \pi^{TAC} \leq 4.03$, $0 \leq \pi^{TAE} \leq 4.00$)

not a substantial change in the results, the introduction of stock effect favours TAE control versus TAC control in terms of net profits because a smaller level of effort is needed to maintain the same level of harvest. Given a smaller level of effort, there is less variation in the harvest level in the TAE, and it is less likely there will be over- or underfishing.

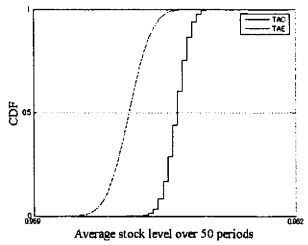
Sensitivity analysis: price elasticity of demand

To investigate how the price elasticity affects the result, different values of the price elasticity of demand ($\delta = 1.3$ and $\delta = 2.1$) are applied. The simulation results are shown in Figures 2.6 and 2.7. Again, the difference to the base-case results in Figures 2.2 and 2.3 are not large. However, Figure 2.6 does show that as the price elasticity increases, the payoffs in terms of net profits increase for TAC versus TAE control. This is because the more responsive is the price

Figure 2.7 **CDF of average biomass with different price elasticity** ($\gamma 2 = 0$)

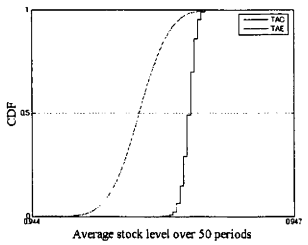
2.7.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$

$\delta = 1.3$



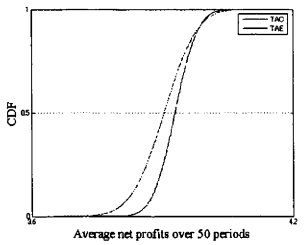
(domain: $0 \leq x \leq 1$)

$\delta = 1.55$



(domain: $0 \leq x \leq 1$)

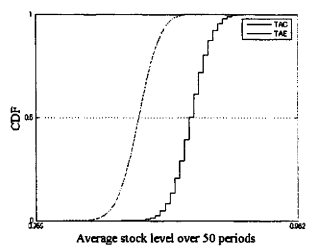
$\delta = 2.1$



(domain: $0 \leq x \leq 1$)

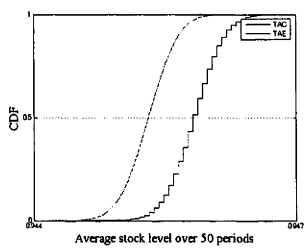
2.7.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$

$\delta = 1.3$



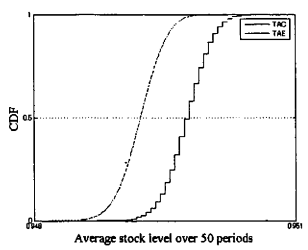
(domain: $0 \leq x \leq 1$)

$\delta = 1.55$



(domain: $0 \leq x \leq 1$)

$\delta = 2.1$



(domain: $0 \leq x \leq 1$)

to change in the harvest the less desirable is a TAE control as it only indirectly controls the harvest.

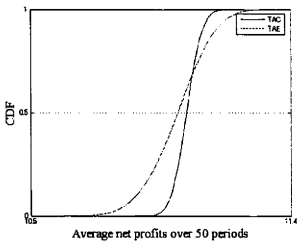
Sensitivity analysis: harvesting costs

Alternative cost parameters ($c = 8$ and $c = 2.4$) are applied to analyse how the results alter with changes in harvesting costs. The simulations are presented in Figures 2.8 and 2.9.[16] The results are very different to Figures 2.2 and 2.3.[17] As the cost parameter decreases, the cost of fishing becomes lower and the optimal harvest level increases. A larger harvest, however, increases the risk of overfishing, and because the TAE control only indirectly limits the harvest, it is optimal to have a lower level of fishing effort to avoid such an outcome. By contrast, the TAC control limits the harvest level directly and there is less need to compensate with lower harvests if it can be controlled directly. Consequently, the TAE is relatively favoured in terms of the average payoffs

Figure 2.8 **CDF of average net profit with different cost parameters** ($\gamma 2 = 0$)

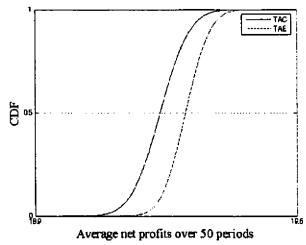
2.8.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$

$c = 14.5$



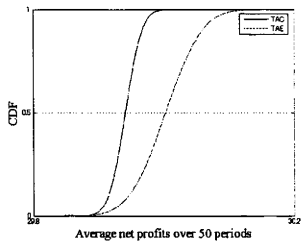
(domain: $0 \leq \pi^{TAC} \leq 11.59$, $0 \leq \pi^{TAE} \leq 11.42$)

$c = 8$



(domain: $0 \leq \pi^{TAC} \leq 20.34$, $0 \leq \pi^{TAE} \leq 20.04$)

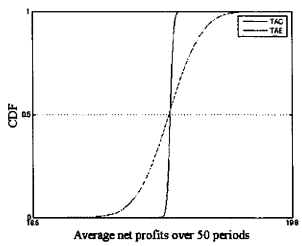
$c = 2.4$



(domain: $0 \leq \pi^{TAC} \leq 40.67$, $0 \leq \pi^{TAE} \leq 40.52$)

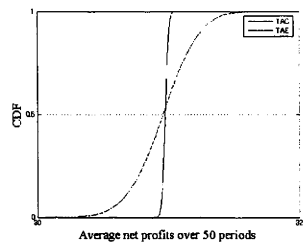
2.8.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$

$c = 14.5$



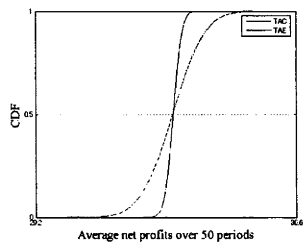
(domain: $0 \leq \pi^{TAC} \leq 11.15$, $0 \leq \pi^{TAE} \leq 11.12$)

$c = 8$



(domain: $0 \leq \pi^{TAC} \leq 19.56$, $0 \leq \pi^{TAE} \leq 19.51$)

$c = 2.4$

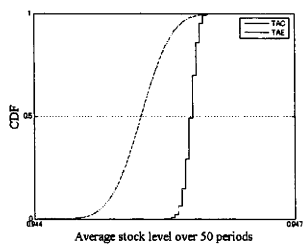


(domain: $0 \leq \pi^{TAC} \leq 40.27$, $0 \leq \pi^{TAE} \leq 40.25$)

Figure 2.9 **CDF of average biomass with different cost parameters** ($\gamma 2 = 0$)

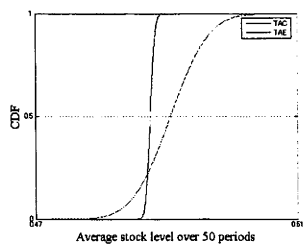
2.9.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$

$c = 14.5$



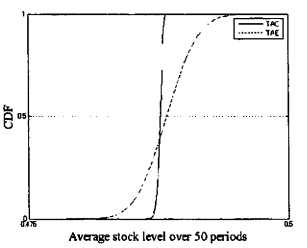
(domain: $0 \leq x \leq 1$)

$c = 8$



(domain: $0 \leq x \leq 1$)

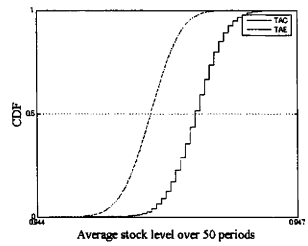
$c = 2.4$



(domain: $0 \leq x \leq 1$)

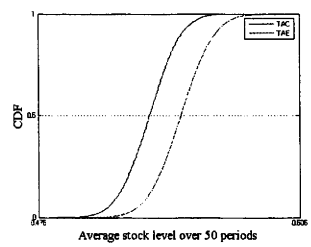
2.9.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$

$c = 14.5$



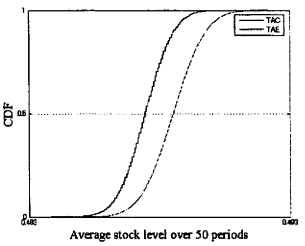
(domain: $0 \leq x \leq 1$)

$c = 8$



(domain: $0 \leq x \leq 1$)

$c = 2.4$



(domain: $0 \leq x \leq 1$)

and generates a higher biomass to the TAC relative to the base case scenario.

Our finding contrasts with the findings of Hannesson and Steinshamn(1991) who show that as fishing cost decreases, the constant effort strategy becomes relatively less profitable than the constant catch management. Their result comes from the fact that they employed a one period model with a strictly convex cost function. By contrast, in our dynamic model with time varying biomass, this relationship does not always hold. For instance, if the constant effort strategy conserves a greater biomass, then the fishing cost with the TAC could be greater than that with the TAE with a stock effect. Thus, in our results, as fishing costs decrease, the TAE level is reduced as it only indirectly controls harvest and the probability of overfishing increases with higher optimal harvests. Consequently, the harvest and effort levels with the TAE become relatively smaller than those with the TAC leading to higher average biomass and net profits relative to TAC control.

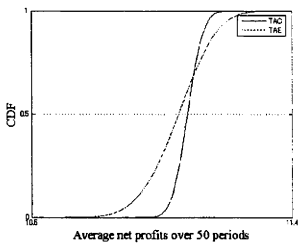
Sensitivity analysis: price effect

A similar result to the cost effect is obtained with higher price parameters of fish ($\bar{p} = 85$ and $\bar{p} = 100$) but with the same price elasticity of demand, as shown in Figures 2.10 and 2.11. As the value of a landed fish increases, the optimal harvest level rises. At a larger harvest the risk of overfishing becomes greater, and because a TAE only controls the harvest indirectly, it is optimal to limit total effort more than total harvest. This is equivalent to a decrease in the cost parameter and favours TAE control relative to TAC control in terms of average net profits and the biomass.

Figure 2.10 **CDF of average net profit with different price parameters** ($\gamma 2 = 0$)

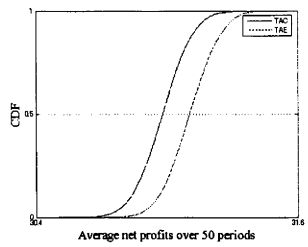
2.10.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$

$\bar{p} = 50$



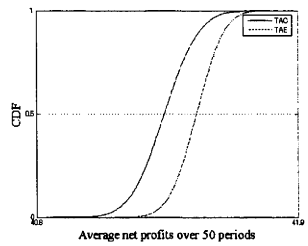
(domain: $0 \leq \pi^{TAC} \leq 11.59$, $0 \leq \pi^{TAE} \leq 11.42$)

$\bar{p} = 85$



(domain: $0 \leq \pi^{TAC} \leq 32.55$, $0 \leq \pi^{TAE} \leq 32.07$)

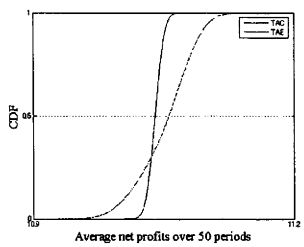
$\bar{p} = 100$



(domain: $0 \leq \pi^{TAC} \leq 44.65$, $0 \leq \pi^{TAE} \leq 44.00$)

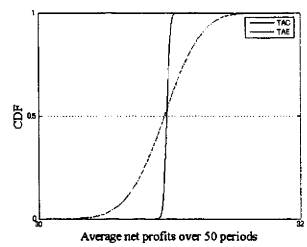
2.10.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$

$\bar{p} = 50$



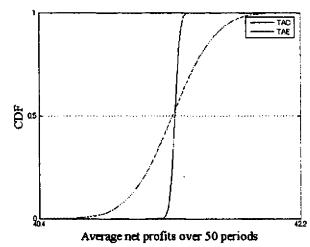
(domain: $0 \leq \pi^{TAC} \leq 11.15$, $0 \leq \pi^{TAE} \leq 11.12$)

$\bar{p} = 85$



(domain: $0 \leq \pi^{TAC} \leq 31.30$, $0 \leq \pi^{TAE} \leq 31.22$)

$\bar{p} = 100$

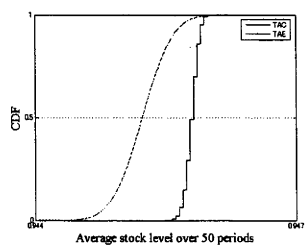


(domain: $0 \leq \pi^{TAC} \leq 42.94$, $0 \leq \pi^{TAE} \leq 42.83$)

Figure 2.11 **CDF of average biomass with different price parameters** ($\gamma 2 = 0$)

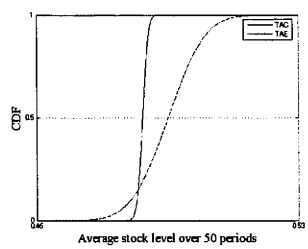
2.11.1 $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$

$\bar{p} = 50$



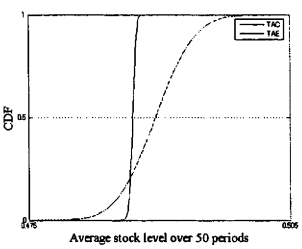
(domain: $0 \leq x \leq 1$)

$\bar{p} = 85$



(domain: $0 \leq x \leq 1$)

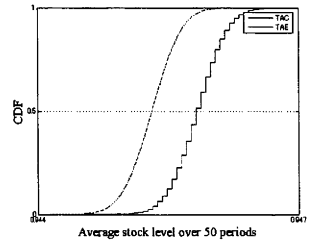
$\bar{p} = 100$



(domain: $0 \leq x \leq 1$)

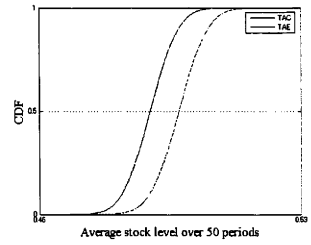
2.11.2 $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$

$\bar{p} = 50$



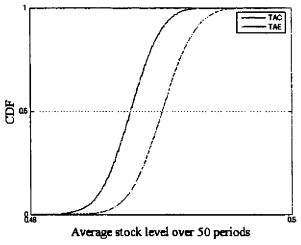
(domain: $0 \leq x \leq 1$)

$\bar{p} = 85$



(domain: $0 \leq x \leq 1$)

$\bar{p} = 100$



(domain: $0 \leq x \leq 1$)

Discussion

The results suggest that, in terms of uncertainty considerations, TAC control is likely to be preferred versus TAE for the Western and Central Pacific skipjack tuna fishery. This is because there is a well-defined and estimated growth function for the fishery and considerable uncertainty in terms of the harvest–effort relationship. For instance, there have been large and unexpected increases in catch per unit of effort in recent years in this fishery (Barclay & Cartwright 2007). Consequently, Figures 2.2.1 and 2.3.1 (corresponding to $\epsilon^g = 0.01$, $\epsilon^h = 0.05$ and $\epsilon^e = 0.05$) are likely to be a better reflection of the differences between TAC and TAE control in the skipjack fishery than Figures 2.2.2 and 2.3.2 (corresponding to $\epsilon^g = 0.05$, $\epsilon^h = 0.01$ and $\epsilon^e = 0.01$). As a result, Figures 2.2.1 and 2.3.1 imply that a TAC control is preferred over a TAE control as it generates both highest expected profits and higher expected stock levels. Changes in the various parameters (stock effect, price elasticity, cost parameter, price effect), however, change the relative desirability of the instruments. Nevertheless, using a price elasticity of 1.55 and a cost parameter of 14.5 obtained from Bertignac et al. (2000), expected net profits still remain higher with a TAC and this result is reinforced the lower is the price of skipjack, which has declined in real terms since the 1980s (Asian Development Bank 2003). Given that the skipjack fishery is not overexploited and its biomass is above its maximum sustained yield and the expected net profits is the primary economic consideration of the purse seine fleet, it would seem that a TAC control is, on the basis of our uncertainty analysis, preferred relative to TAE control for this fishery.

Our findings also contribute to the general literature on instrument choice. By examining multiple uncertainties in an actual fishery using a dynamic model, we show how a decision-making framework in the form of CDFs can be uti-

lized in fisheries management. This approach also offers additional insights. For instance, Hannesson and Steinshamn (1991, p. 88), argue that the most important factor that determines whether a total harvest or total effort control is preferred is the size of the stock effect in the harvest function. Our analysis suggests that other factors, such as the level of the costs and price parameters, are equally important in determining the preferred instrument.

Danielsson (2002) provides the most complete analytical set of results regarding instrument choice but to obtain his finding he was limited to examining the case of only one form of uncertainty—in either the biomass growth function or in terms of catch per unit of effort but not both. By employing numerical methods we are able to examine multiple uncertainties. We stress, however, that our results support the findings of Danielsson (2002) regarding relative size of 'growth' and 'implementation' uncertainties on instrument choice. We also show that modelling several forms of uncertainty is required to make adequate comparisons between the instruments. The only other study to employ a similar approach is Kompas et al. (2008), which they apply to the Northern Tiger Prawn fishery of Australia. However, they do not undertake sensitivity analysis in terms of cost and price parameters or the price elasticity of demand and restrict themselves to comparisons of expected values and standard deviations in the biomass and net profits.

We find that TAC control has the advantage that it results in a lower variation in both biomass and net profits than does a TAE control. However, we also find there are tradeoffs between the harvest level and the risk of overfishing. If the regulator sets a high harvest level, either with a TAC or TAE, the expected net profits will also increase for a given sufficient stock level. On the other hand, higher harvests increase the risk of overfishing and then cause a less optimal biomass level that lowers future net profits. The alternative of harvesting less

today reduces the possibility of overfishing but at the cost of net profits today.

Overall, our analysis provides a decision framework to balance higher expected net profits with lower expected biomass levels and shows how TAC and TAE controls generate different outcomes. Indeed, a key finding of our modelling is that the larger is the harvest level, the greater is the variance in the net profits associated with TAE versus TAC control, but the higher is the expected biomass.

In our modelling, we fix the instrument choice at the beginning period and do not allow for a policy switch. However, even without policy switching, we show that as costs and prices change in a fishery, the relative preference for a given method of control may substantially change. This suggests the possibility that a portfolio of instruments could be applied to optimize the management of fisheries. In such a scenario, fishers could be allocated both shares of a TAE and a TAC. Only one of the instruments would be binding in any period, but it would allow the option to switch into a different policy regime as conditions in the fishery changed. For example, it is planned in the Eastern and Tuna Billfish fishery in Australia that fishers will be assigned shares (denominated in hooks) of a TAE before the end of 2008. However, they could subsequently be allocated individual harvesting rights as a share of TAC should circumstances change to favour the use of individual transferable harvesting rights.

Concluding remarks

One of the most difficult aspects of managing fisheries is to cope with the inherent uncertainties in stock– recruitment and the harvest–effort relationships. Depending on the relative magnitudes of the uncertainties in these relationships and the price and cost parameters, managers can trade-off expected net

profits and biomass levels with their variability.

Using parameter estimates from one of the world's largest fisheries, the Western and Central Pacific skipjack tuna fishery, we analyse multiple uncertainties and compare the use of a total harvest control with a total effort control. Using a decision framework not previously used in this context, we compare the payoffs of the two instruments using cumulative density functions. Under most likely parameter values and given the fishery is not currently overexploited, a total harvest control is favoured to a total effort control if expected net profits are of primary consideration. Nevertheless, a key finding is that neither instrument is always preferred in a world of uncertainty and that a regulator's weighting in terms of the importance of expected net profits versus expected biomass and trade-offs in terms of expected values and variance, will determine the instrument choice.

Our analysis shows that as harvesting costs decrease and the price of fish rises, the desirability of total effort control increases relative to that of a total harvest control in terms of expected net profits and biomass. Overall, our results provide a decision and modelling framework for regulators to compare instruments and to achieve desired management goals.

Appendix

Matlab code for TAE

```
%%%% tae.m
%%%%
%%%% This program solves a dynamic bioeconomic model
%%%% by value function iteration
%%%% Policy instrument: total allowable effort (TAE)
%%%%

close all
clear all
clc

%%%%%%%%%%%%%%%%%%%%
% 1. SET MODEL PARAMETERES
%%%%%%%%%%%%%%%%%%%%

beta = 0.9; % discount rate
n1 = 1.37; % gamma 1
n2 = 0; % gamma 2
n3 = 1.55; % price elasticity of demand
c = 14.5; % cost parameter
p0 = 50; % price parameter
qt = .145; % catchability coefficient
r = 1.31; % intrinsic growth rate
K = 1; % carrying capacity
alpha = 0.89; % parameter in the growth function

% OTHER REQUIRED PARAMETERS
maxit = 1000; % max number of iteration
g = 300; % number of grid
crit = 1e-10; % tolerance criterion
T = 61; % number of periods

% UNCERTAINTY IN THE GROWTH FUNCTION
qg = 10; % size of shock vector
epg = 0.01; % variance of uncertainty
ug = linspace(0,1,qg);

% UNCERTAINTY IN THE HARVEST/EFFORT FUNCTION
qh = 10; % size of shock vector
```

```
eph = 0.05; % variance of uncertainty
uh = linspace(0,1,qh);

%%%%%%%%%%%%%%%%%%%%%%%%%%%
% 2. DISCRETIZATION OF FISH STATE SPACE
%%%%%%%%%%%%%%%%%%%%%%%%%%%

x0 = .5*K; % initial state
xmin = 0; % min of the state
xmax = K; % max of the state
x = [xmin+(0:g-2)*(xmax-xmin)/(g-1) xmax]';

%%%%%%%%%%%%%%%%%%%%%%%%%%%
% 3. CONSTRUCT EXPECTED NET PROFIT SET
%%%%%%%%%%%%%%%%%%%%%%%%%%%

% CALCULATE THE EXPECTED NET PROFIT
% FOR ALL POSSIBLE (x(t),x(t+1)) PAIRS

d = ones(1,g);
zg = 1 + (2*ug - 1)*epg;
zg= zg'*d;
zg = zg(:);
fg = ones(1,g*qg);
zh = 1 + (2*uh- 1)*eph;
zh = d'*zh;
zh = zh(:);
zh = fg'*zh';
clear uh ug d fg

eg = ones(1,qg);
xaux = eg'*x';
xaux = xaux(:);
clear eg

eh = ones(1,qh);
xaux2 = x*eh;
xaux2 = xaux2(:);
clear eh

fg = ones(1,g*qg);
fh = ones(1,g*qh);
W1 = max(zh.*((r*zg.*xaux.*(1 - xaux/K).^alpha + xaux)*fh-...
fg'*xaux2'),0); % harvest
clear zg xaux2
```

```
% W1 (HARVEST) CANNOT EXCEED K
[m,n] = find(W1 > K);
siz = size(m);
for j = 1:siz
W1(m(j,1),n(j,1)) = K;
end

p = p0*(W1).^(-1/n3); % price
R = p.*W1; % total revenue

W2 = ((W1./zh)./(qt*(xaux*fh).^n2)).^(1/n1); % effort
clear W1 xaux fg fh zh

C = c*W2; % total cost
clear W2

nr = max(R - C, 1e-8); % net profit
clear R C

fh = ones(1,g*qh);
d = ones(1,g);
piaux = 1/qh;
piaux = piaux*fh';
pih = piaux*d;
clear d fh piaux;

Ih = eye(g);
Eh = Ih;
for i = 1:qh-1
Eh = [Eh;Ih];
end
clear Ih

Eh = Eh.*pih;
clear pih

nr = nr*Eh; % expected net profit
clear Eh

eg = ones(1,qg);
piaux = 1/qg;
piaux = piaux*eg';
pig = piaux*eg;
clear eg piaux;
```

```
Ig = eye(qg);
Eg = Ig;
for i=1:g-1
Eg=[Eg;Ig];
end
clear Ig

%%%%%%%%%%%%%%%%%%%%%
% 4. VALUE FUNCTION ITERATION
%%%%%%%%%%%%%%%%%%%%%

% INITIAL GUESS OF THE VALUE FUNCTION
V0 = zeros(g*qg,1);

% ITERATION
iconv = 0;
it = 1;

while (iconv==0 && it<maxit)

[V1,G] = max((nr+beta*(Eg*(pig*reshape(V0,qg,g))))');
V1 = V1';
G = G';

error(it) = norm(V0-V1);

if norm(V0-V1)<crit
iconv = 1;
end

V0 = V1;
it = it+1;

end
clear nr

%%%%%%%%%%%%%%%%%%%%%%%%%%
% 5. SIMULATING 'M' SETS OF TIME SERIES
%%%%%%%%%%%%%%%%%%%%%%%%%%

G = reshape(G,qg,g);
M = 50000; % the number of simulations
ug = linspace(0,1,qg);
zg = 1 + (2*ug' - 1)*epg;
```

```
uh = linspace(0,1,qh);
zh= 1 + (2*uh' - 1)*eph;

% DEFINE VARIABLES
thetagm = zeros(T,M);
thetahm = zeros(T,M);
xtm = zeros(T+1,M);
xtbarm = zeros(T+1,M);
etm = zeros(T,M);
htbarm = zeros(T,M);
htm = zeros(T,M);
ctm = zeros(T,M);
ptm = zeros(T,M);
nrtm= zeros(T,M);
indm = zeros(T+1,M);
indbarm = zeros(T+1,M);

eh = ones(1,qh);
piaux = 1/qh; % assume uniform distribution
piaux = piaux*eh';
pih = piaux*eh;
clear eh piaux;

% SIMULATION
for i = 1:M

% CHASE THE MARKOV TRANSITIONS
jg = 1;
iconvg = 0;
auxg = rand;

while (jg <= qg && iconvg == 0)
if auxg < jg/qg
auxg2 = jg;
iconvg = 1;
end
jg = jg+1;
end
thetagm(:,i) = shock(auxg2,pig,T)';

jh = 1;
iconvh = 0;
auxh = rand;

while (jh <= qh && iconvh == 0)
```

```
if auxh < jh/qh
auxh2 = jh;
iconvh = 1;
end
jh = jh+1;
end
thetahm(:,i) = shock(auxh2,pih,T)';

[aux,indm(1,i)] = min(x<x0);
xtm(1,i) = x(indm(1,i));

for j = 1:T

[aux, indm(j,i)] = min(x<xtm(j,i));
indbar(j+1,i) = G(thetagm(j,i),indm(j,i));

xtbarm(j+1,i) = x(indbar(j+1,i));
htmbar(j,i) = max(zg(thetagm(j,i))*r*xtm(j,i)*(1 - xtm(j,i)/K)^alpha +
xtm(j,i) - ...
xtbarm(j+1,i), 0);
etm(j,i) = (htmbar(j,i)/(qt*xtm(j,i)^n2))^(1/n1);
htm(j,i) = zh(thetahm(j,i))*qt*etm(j,i)^n1*xtm(j,i)^n2;
xtm(j+1,i) = r*zg(thetagm(j,i))*xtm(j,i)*...
(1 - xtm(j,i)/K)^alpha - htm(j,i) + xtm(j,i);
ptm(j,i) = p0*htm(j,i)^(-1/n3);
nrtm(j,i) = ptm(j,1)*htm(j,i) - c*etm(j,i);

% EXCLUDE NEGATIVE NP

if nrtm(j,i) < 0
nrtm(j,i) = 0;
htm(j,i) = 0;
etm(j,i) = 0;
xtm(j+1,i) = r*zg(thetagm(j,i))*xtm(j,i)*...
(1 - xtm(j,i)/K)^alpha + xtm(j,i);
end

end

end
```

Matlab code for TAC

```
%%%% tac.m
%%%%
% %%% This program solves a dynamic bioeconomic model
%%%% by value function iteration
%%%% Policy instrument: total allowable catch (TAC)
%%%%

close all
clear all
clc

%%%%%%%%%%%%%%%%%%%%
% 1. SET MODEL PARAMETERES
%%%%%%%%%%%%%%%%%%%%

beta = 0.9; % discount factor
n1 = 1.37; % gamma 1
n2 = 0; % gamma 2
n3 = 1.55; % price elasticity of demand
c = 14.5; % cost parameter
p0 = 50; % price parameter
qt = .145; % catchability coefficient
r = 1.31; % intrinsic growth rate
K = 1; % carrying capacity
alpha = 0.89; % parameter in the growth function

% OTHER REQUIRED PARAMETERS
maxit = 1000; % max number of iteration
g = 300; % number of grid
crit = 1e-10; % tolerance criterion
T = 61; % number of periods

% UNCERTAINTY IN THE GROWTH FUNCTION
qg = 10; % size of shock vector
epg = 0.01; % variance of uncertainty
ug = linspace(0,1,qg);

% UNCERTAINTY IN THE HARVEST/EFFORT FUNCTION
qh = 10; % size of shock vector
eph = 0.05; % variance of uncertainty
uh = linspace(0,1,qh);
```

```
%%%
```

```
p = p0*(W1).^(-1/n3); % price

R = p.*W1; % total revenue

d = ones(1,g);
ze = 1 + (2*ue- 1)*epe;
ze = d'*ze;
ze = ze(:);
ze = fg'*ze';
clear ue d fg

W2 = ze.*((W1./(qt*(xaux*fe).^n2)).^(1/n1)); % effort
clear W1 xaux fe

C = c*W2; % total cost clear W2

nr = max(R - C, 1e-8); % net profit
clear R C

fe = ones(1,g*qe);
d = ones(1,g);
piaux = 1/qe;
piaux = piaux*fe';
pie = piaux*d;
clear d fe piaux;

Ie = eye(g);
Ee = Ie;
for i = 1:qe-1
Ee = [Ee;Ie];
end
clear Ie
Ee = Ee.*pie;

nr = nr*Ee; % expected net profit
clear Ee pie

eg = ones(1,qg);
piaux = 1/qg;
piaux = piaux*eg';
pig = piaux*eg;
clear eg piaux;

Ig = eye(qg);
Eg = Ig;
```

```
for i=1:g-1
Eg=[Eg;Ig];
end
clear Ig

%%%%%%%%%%%%%%%%%%%%
% 4. VALUE FUNCTION ITERATION
%%%%%%%%%%%%%%%%%%%%

% INITIAL GUESS OF THE VALUE FUNCTION
V0 = zeros(g*qg,1);

% ITERATION
iconv = 0;
it = 1;

while (iconv==0 && it<maxit)

[V1,G] = max((nr+beta*(Eg*(pig*reshape(V0,qg,g))))');

V1 = V1';
G = G';

error(it) = norm(V0-V1);

if norm(V0-V1)<crit
iconv = 1;
end

V0 = V1;
it = it+1;

end
clear nr

%%%%%%%%%%%%%%%%%%%%%%%%%
% 5. SIMULATING 'M' SETS OF TIME SERIES
%%%%%%%%%%%%%%%%%%%%%%%%%

G = reshape(G,qg,g);
M = 50000; % the number of simulations
ug = linspace(0,1,qg);
zg = 1 + (2*ug' - 1)*epg;
ue = linspace(0,1,qe);
ze= 1 + (2*ue' - 1)*epe;
```

```
% DEFINE VARIABLES
thetagm = zeros(T,M);
thetaem = zeros(T,M);
xtm = zeros(T+1,M);
etm = zeros(T,M);
htm = zeros(T,M);
ctm = zeros(T,M);
ptm = zeros(T,M);
nrtm= zeros(T,M);
indm = zeros(T+1,M);

ee = ones(1,qe);
piaux = 1/qe;
piaux = piaux*ee';
pie = piaux*ee;
clear ee piaux;

% SIMULATE

for i = 1:M

% CHASE THE MARKOV TRANSITIONS
jg = 1;
iconvg = 0;
auxg = rand;

while (jg <= qg && iconvg == 0)
if auxg < jg/qg
auxg2 = jg;
iconvg = 1;
end
jg = jg+1;
end
thetagm(:,i) = shock(auxg2,pig,T)';

je = 1;
iconve = 0;
auxe = rand;

while (je <= qe && iconve == 0)
if auxe < je/qe
auxe2 = je;
iconve = 1;
end
```

```
je = je+1;
end
thetaem(:,i) = shock(auxe2,pie,T)';

[aux,indm(1,i)] = min(x<x0);
xtm(1,i) = x(indm(1,i));

for j=1:T

[aux, indm(j,i)] = min(x<xtm(j,i));
indbar(j+1,i) = G(thetagm(j,i),indm(j,i));

xtm(j+1,i) = x(indbar(j+1,i));
htm(j,i) = max(zg(thetagm(j,i))*r*xtm(j,i)*(1 - xtm(j,i)/K)^alpha +
xtm(j,i) - ...
xtm(j+1,i), 0);
etm(j,i) = ze(thetaem(j,i))*((htm(j,i)/(qt*xtm(j,i)^n2))^(1/n1));
ptm(j,i) = p0*htm(j,i)^(-1/n3);
nrtm(j,i) = ptm(j,i)*htm(j,i) - c*etm(j,i);

% EXCLUDE NEGATIVE NP
if nrtm(j,i) < 0
nrtm(j,i) = 0;
htm(j,i) = 0;
etm(j,i) = 0;
xtm(j+1,i) = r*zg(thetagm(j,i))*xtm(j,i)*...
(1 - xtm(j,i)/K)^alpha + xtm(j,i);
end

end

end
```

Endnotes

[1] Francis and Shotton (1997) discuss different types of 'risk' in fisheries management. The uncertainty in this chapter can be categorised as *model uncertainty* in the Frincis and Shotton's six types of uncertainty. In other words, the uncertainty arises from the lack of complete information about the structure of the fishery (e.g., stock-recruitment relationship and effort-harvest relationship).

[2] The relative costs in monitoring catch and effort depends on, for example, whether the fishery is a multi-species fishery and the selectivity of fishing gears. For instance, if the fishery is a single species fishery and exhibits strong selectivity for fishing gears, the cost of monitoring catch is likely to be lower than that of monitoring effort.

[3] This research question is important because, when different policy instruments are compared in an uncertain environment, expected values only provide a single reference point that would produce misleading results. Francis and Shotton (1997) discuss the problem and complexity of different performance measures in a stochastic environment.

[4] It is important to note that prawn fisheries often have a very uncertain relationship between the fish stock and the level of recruitment since the recruitment can be dependent on rainfall.

[5] The parameter $\gamma 1$ is estimated as $\gamma 1 = 1.37$, thus the restriction, $3.7 > \delta > 1$ is necessary to ensure the strict concavity of the profit function. Under this restriction the harvest and effort functions are, respectively, strictly convex and concave and the revenue and cost functions are concave with respect to the control variables.

[6]As with most other fisheries, the skipjack fishery is a multi-species fishery and bycatch problems exist. However, this fishery is a good application to our

model because skipjack is a relatively well-targeted species. We also note that in multi-species fisheries TAE control may lead to economic over (and under) fishing for some of the species in the absence of other forms of control.

[7]See Judd (1998) for further details.

[8] See Appendix for Matlab code.

[9]The deterministic case is provided to show that a solution exists and that the system is stable but it is not a benchmark.

[10] In this chapter we use the net profits and biomass as performance measures between TAC and TAE controls. Alternatively, it is possible to directly compare the catches and effort.

[11]This result is consistent with the findings of Hannesson and Steinshamn (1991).

[12]The same realizations in terms of the random variables are applied for both TAC and TAE controls.

[13]The figures of the optimal time paths with $\epsilon^g = \epsilon^h = \epsilon^e = 0.05$ and $\epsilon^g = \epsilon^h = \epsilon^e = 0.01$ are available upon request. The key insights are the same as in Figure 2.1.

[14]Note that the simulated stock level is the biomass consistent with a dynamic maximum economic yield (B_{MEY}). The average biomass is close to the carrying capacity in Figures 2.3.1 and 2.3.2 which is dues to the relative size in the price and cost parameter and also reflects that the fishery is, at present, not overexploited biologically.

[15]For example, Kompas and Che (2006) estimated a harvest function that shows the relationship between the harvest and biomass in three of the tuna

fisheries in the Western and Central Pacific while Grafton et al. (2007) provide such estimates for bigeye and yellowfin tuna in the same fishery.

[16]Because the density of the biomass is close to unity with benchmark parameters, sensitivity analysis that involves a higher price and lower cost (and thus a higher catch) provides a more useful comparison of the two policy instruments.

[17] Note that the changes in the difference between the average biomass in the TAE and TAC controls in Figure 2.9.1 are not consistent. The reason for this inconsistent behaviour is not clear from the figures and a further analysis is needed.

Chapter 3

Marine reserves switching with non-market values under uncertainty

Introduction

In the last two decades, the use of marine reserves has received increased attention as a strategy to solve management failures in fisheries. There is theoretical and empirical evidence of various biological and socio-economic benefits from closing a fishing ground.[1] For example, reserves can; 1) increase spawning biomass and population abundance; 2) improve habitat quality; 3) have a positive spillover effect from the reserve to harvested populations; 4) generate less variation in biomass and catch; 5) stimulate knowledge in marine biology and oceanography; 6) enhance tourism and recreational activities while protecting cultural heritage; and 7) act as insurance against catastrophe such as recruitment failure and unexpected variations in marine environments (Guénette et al. 1998; Hilborn et al. 2004).

In contrast, it has been more controversial whether reserves can increase the total harvest in a fishery (Holland & Brazee 1996; Hannesson 1998 and 2002;

Sumaila 1998). As a result of creating reserves, the overall fishing area decreases and thereafter the total harvest falls, especially in open access fisheries. Previous studies, however, have found that reserves can increase economic payoffs under some conditions, such as, if fish stocks are overexploited (Pezzey et al. 2000; Rodwell & Roberts 2004), if the foregone benefit from closing an area is lower than the benefit of positive spillovers from the reserve (Sanchirico & Wilen 2001; Sanchirico et al. 2006) and if a large negative shock is realised in the biomass. Acting as a hedge against a large negative shock, reserves can increase the economic payoff from fisheries even if harvest and effort levels are optimally controlled (Grafton et al. 2006b). Costello and Polasky (2008) also show that it is optimal to close the fishing ground for stock recovery if the fish stock falls below the targeted escapement level by large stochastic variations.

The purposes of this paper are; 1) to develop a tractable bioeconomic model for marine reserves switching under an uncertain environment; 2) to investigate the effect of introducing a switching strategy and compare this with alternative policy scenarios; and 3) to analyse how the non-market value of reserves affects the reserve management. To accomplish these objectives, this paper employs a stochastic dynamic programming approach and we apply the developed model to the red throat emperor fishery in the Great Barrier Reef of Australia. In the switching strategy, a non-fishing area is rotated from one site to another according to economic criteria through time. While a number of previous studies have discussed whether reserves should be created and what their consequences would be, much less is known about whether reserves should be fixed at a single site or should be flexibly rotated from one site to another, corresponding to changes in the environment. Moreover, most previous studies examine the effect of permanent fishing closure at one site, whereas the switching strategy has not been clearly investigated.[2]

Another important issue regarding marine reserves is the non-market value of reserves. Reserves often create significant non-use and amenity values because closing fishing grounds improves habitat quality and biodiversity in the environment and this results in sustaining the ecosystem as well as natural based tourism in the community. The rise in the non-market value of reserves will consequently increase total economic returns in the fishery. Hence, it is important to take into account the non-market value of reserves in the decision making process. Several studies estimate the value of marine reserves by incorporating non-market valuation methods. Bhat (2003), for example, estimates that reserve-induced reef quality improvements could increase the use values of the reserve in Florida Keys of the U.S. by 69 per cent. By estimating a recreational demand curve in the Great Barrier Reef of Australia, Kragt et al. (2006) also show that welfare loss due to environmental degradation will be significant. Although there are previous bioeconomic studies on the non-market value of forestry (Hartman 1976; Swallow et al. 1997), as far as we are aware, this paper is the first study to develop a bioeconomic model of the non-market value of marine reserves.

The paper is organised as follows. In Section 3.2, a stochastic bioeconomic model of marine reserves switching incorporating the non-market value of reserves is developed. The simulation method is also discussed. Section 3.3 describes the red throat emperor fishery in the Great Barrier Reef of Australia and discusses the parameter values applied to the developed model. Section 3.4 shows the numerical results of the model without the non-market value of reserves. Section 3.5 discusses how the introduction of the non-market value would affect the results. The last section provides concluding remarks.

The model

Biological model

Space. Spatial features are modeled by a metapopulation model, in which discrete patches represent a fish habitat and the size of patches is determined by the carrying capacity. As in other metapopulation models (for example, Sanchirico & Wilen 1999), this paper assumes that the distance between patches is identical and fixed, the size of each patch is constant and the transfer function $T_{ij}(\mathbf{x})$ captures the various forms of fish dispersal processes between patches. Here, $\mathbf{x} = (x^1\ x^2\ \cdots\ x^n)$ denotes the vector of fish stocks and $i, j \in \mathcal{N}$ is the site index, $\mathcal{N} = \{1, 2, \ldots, n\}$.

Population dynamics. Time is discrete, indexed by $t \in \mathbb{N}$. The population dynamics in site $i \in \mathcal{N}$ at time t are modelled as:

$$x^i_{t+1} = x^i_t - h^i_t + z^{gi}_t r x^i_t\Big(1 - \frac{x^i_t}{K^i}\Big) + \sum_j^{j\neq i} T_{ij}(\mathbf{x}) - z^{si}_t x^i_t, \text{ if site } i \text{ is open; and}$$

$$x^i_{t+1} = x^i_t + z^{gi}_t r x^i_t\Big(1 - \frac{x^i_t}{K^i}\Big) + \sum_j^{j\neq i} T_{ij}(\mathbf{x}), \text{ if site } i \text{ is closed.} \tag{3.1}$$

where x^i_t is the fish stock and K^i is the carrying capacity in site i. The first term is the escapement in each period. If site i is a fishing ground, the fish stock is exploited by the harvest level $h^i_t > 0$, whereas $h^i_t = 0$ if a reserve is placed on the site. The second term represents the density dependent growth function with the intrinsic growth rate r. The third term is the fish transfer function. The term z^{gi}_t represents stochastic variations in fish growth at site i (growth uncertainty) and z^{si}_t is a large negative shock that is proportional to the fish stock. Assume that negative shocks are only realized in fishing

grounds due to fishing activities. This assumption reflects empirical evidence that there is a higher risk of habitat destruction and stock-recruitment failure in a fishing ground than in a reserve (Goñi 1998; Turner et al. 1999; Jennings et al. 2001).

Uncertainties. The growth uncertainty is specified as $z^g = 1 + (2u - 1)\epsilon$, where u is a uniformly discretised grid. The term ϵ determines the size of variations and lies between 0 and 1, indicating from 0 per cent to 100 per cent variation. It is assumed that z^g follows a Markov process with the same transition probabilities between each state. The large negative shock z^s is specified as:

$$z_t^s(\omega_t) = \begin{cases} 0 & \text{if } \omega_t = 1 \text{ (shock is not realised)} \\ \alpha & \text{if } \omega_t = 2 \text{ (shock is realised)} \end{cases} \tag{3.2}$$

If the indicator variable ω_t is 2 at time t, then the negative shock is realised, otherwise there is no shock. The size of the negative shock is proportional to the stock level that is determined by parameter α.

Transfer function. The transfer function captures the characteristics of fish flow from one site to another. It is important to consider fish dispersal, since the spatial features and the policy implications of marine reserves significantly depend on the linkages between sites (Sanchirico & Wilen 2001; Sanchirico et al. 2006). In the closed process, there are no interactions between sites and the biomass in each site is determined only by the own growth and harvest rate. In the fully integrated open process, on the other hand, each site is interconnected and allows temporary local extinction of the fish stock as well as stock recoveries through fish transfer from another site. In the closed system, however, stock recovery does not happen once the fish stock falls to zero.

Assume that the fish flow depends on the relative density of the biomass between the sites. Following previous studies (for example, Conrad 1999; Sanchirico & Wilen 2001; Grafton et al. 2006b), the transfer function is specified as:

$$T_{ij}(\mathbf{x}) = mK^i\left(\frac{x^j}{K^j} - \frac{x^i}{K^i}\right) \quad \text{if } i \text{ and } j \text{ are adjecent,} \tag{3.3}$$

where m is the transfer coefficient. Assuming that the size of each site is identical, the transfer function can be reduced to $m\,(x^j - x^i)$. In this case, the transfer coefficient, m, represents the migration rate, which is the fraction of the difference in biomass between sites i and j.

Economic model

Suppose that $\Gamma \subseteq \mathcal{N}$ is a set of the sites that are open for fishing, then, the net profit at time t is defined as:

$$\pi_t^{np} = p(h_t)h_t - \sum_{i\in\Gamma} c(x_t^i)h_t^i, \tag{3.4}$$

where $h = \sum_{i\in\Gamma} h^i$, $p(\cdot)$ is the inverse demand function and $c(\cdot)$ is the cost function. The inverse demand and cost functions are defined as, respectively:

$$p(\cdot) = \bar{p}h_t^{-1/\delta} \text{ and } c(\cdot) = \bar{c}/x_t^i \tag{3.5}$$

where δ is the constant price elasticity of demand and $\bar{p}$ and $\bar{c}$ are parameters. Note that this demand function form can capture the various forms of demand. If $0 < \delta < \infty$, for example, $p_h < 0$, hence the demand curve is downward sloping, whereas the price is constant if $\delta \to \infty$. For the cost function $c_x < 0$ and $c_{xx} > 0$. Thus, the total fishing cost decreases in the biomass and the decreasing rate is progressive.

The location of reserve is the regulator's control variable, which is optimally

chosen. The harvest level is sub-optimally controlled by setting a rule-of-thumb total allowable catch (TAC). Also, in the presence of various forms of uncertainty, a constant escapement policy is not likely to be the optimal harvesting strategy, but the policy function is a function of the biomass (Sethi et al. 2005). Thus, we employ a feedback control policy where the harvest in each patch is a fraction of the biomass. In other words $h_t^i = \theta x_t^i$ if $i \in \Gamma$, but $h_t^i = 0$ if $i \notin \Gamma$.[3] Varying the value of θ, the effect of different levels of harvest pressure can be analysed.

Non-market value of reserves

We suppose that the non-market value of marine reserves is a function of a weighted average of the population density and length of closing a fishing ground. In other words, $\Phi = \alpha_3 \cdot (x/K) + (1 - \alpha_3) \cdot \tau$ where $\alpha_3 \in [0, 1]$ is a weighting parameter and $\tau \in \{0, 1, 2, \ldots\}$ is the length of closing a site. To make the two terms, x/K and τ, consistent, τ is redefined on the $[0, 1]$ interval and thus $\Phi \in [0, 1]$. We assume that $\alpha_3 = 0.5$. The non-market value function is then defined as:

$$\pi_t^{nmkt}(\Phi_t) = \frac{\alpha_0}{1 + e^{[\alpha_1 - \alpha_2 \Phi(x_t, \tau_t)]}}, \ \alpha_0, \alpha_1, \alpha_2 > 0 \tag{3.6}$$

This is a logistic function where $\partial \pi^{nmk} / \partial \Phi > 0$. The parameter α_0 represents the maximum value of π^{nmkt}, and α_1 and α_2, respectively, determine the curvature of the function and the speed of reaching the maximum value. With this function form, the non-market value of reserves initially increases in a progressive way as Φ rises, while the rate of increase diminishes when the value becomes closer to the maximum value. In other words, when Φ is small the function is strictly convex and the function becomes strictly concave after Φ reaches a certain value. After the non-market value reaches to the maximum

value, the value remains at the maximum value as Φ increases.

Dynamic optimisation model

The objective function for the regulator's optimization problem is the sum of the discounted net profit from exploiting the fish stock and the non-market value of creating reserves over time ($\sum_t \pi_t^* = \sum_t \left(\pi_t^{np} + \pi_t^{nmkt}\right)$). The regulator aims to maximise the discounted total return over an infinite time horizon. The future return is discounted with the discounting factor $\beta \in (0,1)$. This paper considers a case with two sites and supposes that site 1 is initially closed. The maximisation problem is then defined as:

$$\max \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \pi_t^*$$

$$\text{subject to} \begin{cases} x_{t+1}^1 = x_t^1 + z_t^{g1} r x_t^1 \left(1 - \frac{x_t^1}{K^1}\right) + m\left(x_t^2 - x_t^1\right) \\ x_{t+1}^2 = x_t^2 - h_t^2 + z_t^{g2} r x_t^2 \left(1 - \frac{x_t^2}{K^2}\right) - z_t^{s2} x_t^2 - m\left(x_t^2 - x_t^1\right) \\ x_0^i = x^i(0), \quad z_0^{gi} = z^{gi}(0), \text{ and } z_0^{si} = z^{si}(0), \ i = 1,2 \end{cases} \tag{3.7}$$

The Bellman equation is:

$$V(\mathbf{x_t}, \mathbf{z_t^g}, \mathbf{z_t^s}) = \max \Big\{ \pi^*(x_t^2) + \beta \mathbb{E}_0 V(\mathbf{x_{t+1}}, \mathbf{z_{t+1}^g}, \mathbf{z_{t+1}^s}), \\ \pi^*(x_t^1) - \kappa(\pi^*(x_t^2)) + \beta \mathbb{E}_0 V(\mathbf{x_{t+1}}, \mathbf{z_{t+1}^g}, \mathbf{z_{t+1}^s}) \Big\} \tag{3.8}$$

where $\mathbb{E}_0$ is the mathematical expectation operator and $\mathbf{x}$, $\mathbf{z^g}$ and $\mathbf{z^s}$ are the vectors of the fish stock, stochastic variations in fish growth and negative shock, respectively. The term $\kappa(\cdot)$ is the transaction cost function of rotating the reserve. We assume that the transaction cost is a function of the foregone profit by closing the area and $d\kappa/d\pi^{*i} > 0$. This reflects that the opportunity

cost of closing a fishing ground increases as the forgone profit of fishing in the area increases. We also assume that the cost is proportional to the profit, thereby, $\kappa(\pi^{*i}) = \kappa_0 \pi^{*i}$, where $\kappa_0 \in [0, 1]$. The greater the parameter κ_0 the higher is the transaction cost.

The value function $V(\cdot)$ (the left hand side of equation (3.8)) represents the maximum attainable objective function at time t. The first term on the right hand side of the equation, $\pi^*(\cdot)$, is the total return if site 1 is continuously closed. The next term $\beta \mathbb{E}_0 V(\cdot)$ represents the discounted expected value function at time $t+1$. The first expression, $\pi^*(\cdot)+\beta \mathbb{E}_0 V(\cdot)$, is thus the overall total return when site 1 is closed. The second expression $\pi^*(\cdot) - \kappa(\cdot) + \beta \mathbb{E}_0 V(\cdot)$, represents the overall total return when the reserve is rotated.

Simulation method

Due to the complexity of the model, the analytical solution of the optimization problem would not exist. Thus, the problem is numerically solved by approximating the value function with the collocation method.[4] In other words, $V(\mathbf{x}, \mathbf{z^g}, \mathbf{z^s}) \approx \sum_{l=1}^{L} k_l \phi_l$, where ϕ is a degree L polynomial basis function with coefficients k and,

$$V(\mathbf{x}, \mathbf{z^g}, \mathbf{z^s}) \approx \max_y \Big\{ \pi(x^2) + \beta \sum_{l=1}^{L} \sum_{m=1}^{M} \sum_{q=1}^{Q} w_m^g w_q^s k_l \phi_l(\mathbf{x}, \mathbf{z}_m^g, \mathbf{z}_q^s), \\ \pi(x^1) - \kappa(\pi(x_t^2)) + \beta \sum_{l}^{L} \sum_{m}^{M} \sum_{q}^{Q} w_m^g w_q^s k_l \phi_l(\mathbf{x}, \mathbf{z}_j^g, \mathbf{z}_q^s) \Big\} \tag{3.9}$$

where w_m^g and w_q^s are the probabilities of the realisation of each state in the growth uncertainty and negative shock, respectively. Growth uncertainty z^g is discretised with 10 grids ($M = 10$) and the negative shock z^s is discretised with two grids ($Q = 2$). This paper uses the Chebyshev polynomials as the

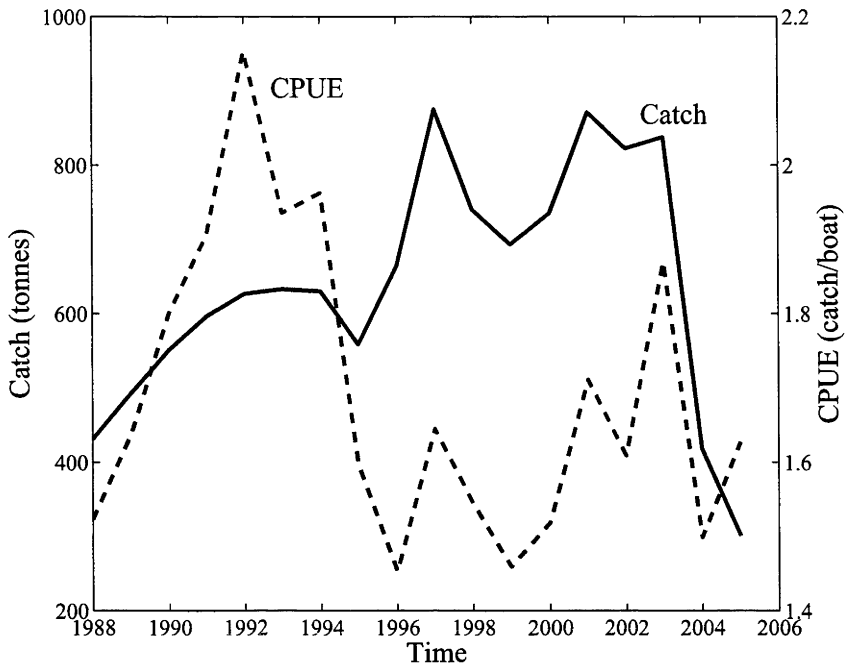
basis function.

Red throat emperor fishery in Australia

The model developed in the previous section is applied to the red throat emperor fishery in the Great Barrier Reef (GBR) of Queensland, Australia. The red throat emperor (*Lethrinus miniatus*) is a secondry target species for both the commercial and recreational sectors in the Coral Reef Fin Fish Fishery (CRFFF) of the GBR. The major fishing method is hook and line gear for all sectors and spear for the recreational sector. The fishery is currently overseen by the Queensland Department of Primary Industries & Fisheries (DPI&F) and regulated under Queensland's Fisheries (Coral Reef Fin Fish Fishery) Management Plan 2003. The fishery is managed by setting the total allowable catch (TAC) with individual transferable quotas (ITQs) for the commercial catch and by regulating the minimum legal size (Leigh et al. 2006). Moreover, since the fishery operates within the Great Barrier Reef World Heritage Area (GBRWHA), the Great Barrier Reef Marine Park Authority (GBRMPA) also imposes management measures on the fishery including temporary and permanently closing a fishing ground (Williams 2003).

Figure 3.1 shows the changes in catch and catch per unit of effort (CPUE) of the fishery over time. Before the introudction of ITQs in 2004 the annual catch increased approximately four times between 1980 and 2003, creating concern about the long-term sustainability of the fishery (Leigh et al. 2006). In contrast, the catch per unit of effort dropped dramatically in the mid 1990s. This decline could be due to a recruitment failure in the fish stock during the period.[5] The price of red throat emperor is relatively stable. For example the gross value of production, the fish price received by the fisher at landing, is

Figure 3.1 **Catch and CPUE over time**



constant at around A$5,000 per tonne (CHRIS 2008) and the market price of whole red throat emperor stays at around A$4 (Little et al. 2009).

To simulate the developed model in Matlab,[6] the values for the biological parameters are obtained from Leigh et al. (2006). The intrinsic growth rate (r) is 0.12 and the carrying capacity (K) is 6,913 tonnes. Since the price of red throat emperor at landing is relatively stable at around A$5,000 per tonne, we assume that the elasticity of demand is infinite and the price parameter is 5. In the absence of adequate data, the parameters in the cost function and transfer coefficient are initially set at $\bar{c} = 2$ and $m = 0.1$ and the sensitivity analysis of changes in these parameters is undertaken. The harvest fraction is initially arbitrary set at $\theta = 0.08$ and the effect of changes in the parameter is also tested.[7] The parameter in growth uncertainty is $\epsilon = 0.05$ and the arrival rate of the negative shock is 0.04 and the size of the shock is $\alpha = 0.13$. The time discounting rate is 10 per cent.

Numerical results without non-market value of reserves

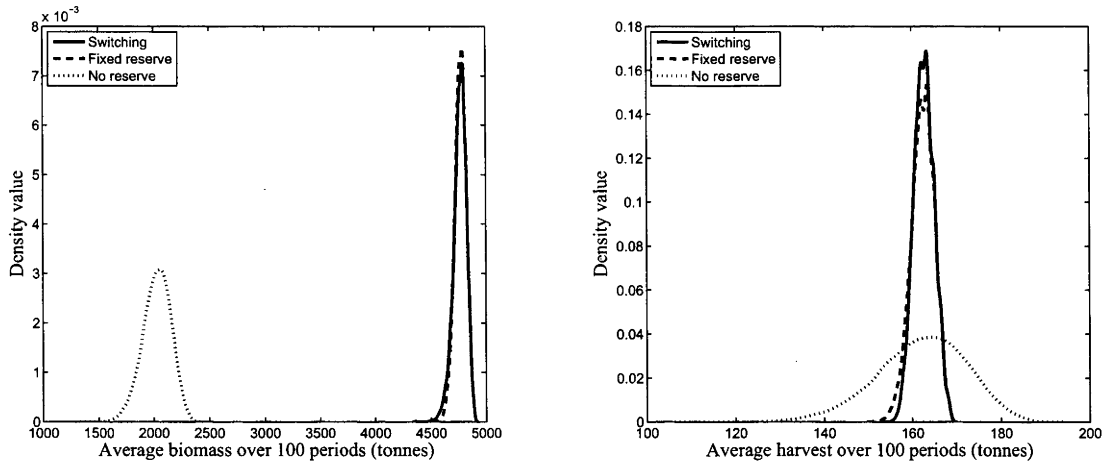
In this section, we analyse the marine reserves switching without the non-market value of marine reserves, by comparing the switching strategy with alternative policy scenarios. Before introducing the non-market value of reserves, it is important to examine what policy results the switching strategy would induce, how they differ from other policy scenarios and how the optimal switching rule varies depending on changes in the biological and economic parameters.

Comparisons in harvest and biomass under different policy scenarios

Open process. The density distribution of the biomass and harvest is, respectively, presented in Figure 3.2 for three policy scenarios: marine reserves switching, fixed reserve and no-reserve cases. In the fixed reserve case, the non-fishing area is permanently fixed at a single site, whereas, in the no-reserve case, the reserve is not created at all times. Figure 3.2 shows that the management with reserves produces a significantly higher biomass. Figure 3.2 also shows two important functions the reserve possesses. First, the reserve works as a buffer against stochastic variations and second, fish dispersal from the reserve to harvested populations smooth the average biomass over sites. As a result, the management with reserves generates a smaller variance in both the biomass and harvest. Moreover, due to these two effects, the total harvest in the management with reserves could become greater than that in the no-reserve case. This result is consistent with previous studies, such as Lauck et al. (1998); Grafton et al. (2006b); Costello and Polasky (2008). Acting as a hedge against large stochastic variations, reserves increase the total harvest.

Where the switching and fixed reserve strategies are compared, although the difference is not large in this case, the biomass is likely to become higher in

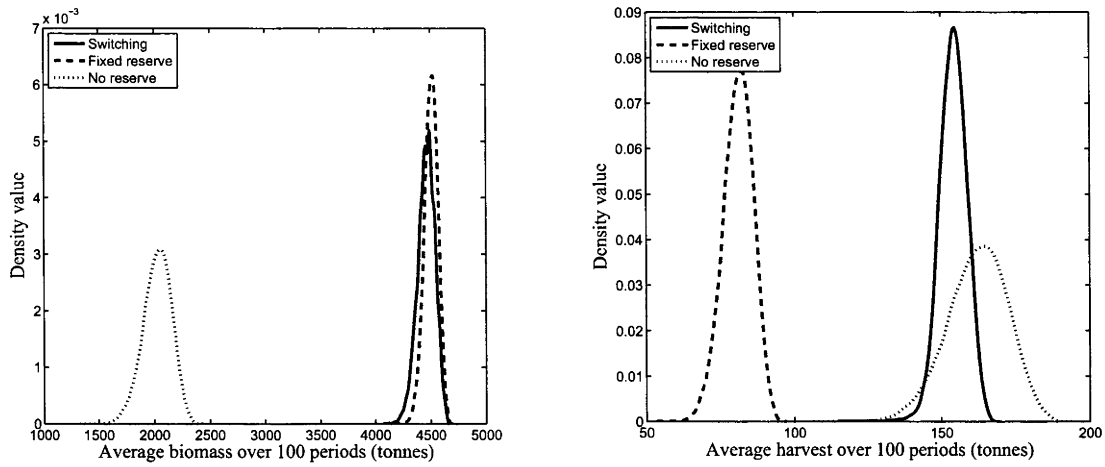
Figure 3.2 **Density distributions of biomass and harvest** ($m = 0.1$, $\theta = 0.08$)



the fixed reserve case. The harvest is, on the other hand, more likely to be greater in the switching strategy. In the switching strategy fishing grounds are rotated to a more profitable area. Consequently, the switching strategy generates a greater catch than the fixed reserve case, but results in a smaller biomass. It is important to note that, in Figure 3.2, the difference between the switching and fixed reserve case is not significant, but the difference could be large depending on the biological and economic parameters. This will be discussed next.

Closed process. The density distribution of the biomass and harvest under the closed dispersal process for the three policy scenarios are compared in Figure 3.3, respectively. The density distribution of the biomass is similar to that under the open process. Since one of the fishing grouds is closed, the management with reserves generates a higher biomass than the no-reserve case. Also, the biomass in the fixed reserve case is likely to be greater than that in the switching strategy. This is because the fishing area is rotated to a more profitable area in the switching strategy and, as a result, the total fish stocks are more exploited. In the closed process the reserve still works as a buffer against stochastic variations and this makes the variations in the biomass and harvest in the management with reserves smaller than those in the no-reserve

Figure 3.3 **Density distributions of biomass and harvest under the closed process** ($m = 0$, $\theta = 0.08$)



case.

In contrast, when there are no linkages between sites, there is no fish dispersal from the reserve to harvested populations, thus the reserve does not smooth the average biomass over sites. The harvest in the fixed reserve case is much lower than that in the other two cases. Without a reasonable volume of fish flow, the total harvestable population becomes significantly small in the fixed reserve case. In other words, when there are only relatively weak linkages between sites, large trade-offs exist between the harvest and biomass in the fixed reserve case. In contrast, switching the reserve can decrease the degree of trade-off between the harvest and biomass. By rotating a non-fishing area over time, the switching strategy maintains a relatively high catch level as well as fish stocks, even if there are only weak linkages between adjacent sites.

Sensitivity analysis

The difference in the biomass and harvest between various policy scenarios depends on the relative size of the biological and economic parameters. As shown in the previous subsection, the biomass is always the highest in the fixed reserve case and the smallest in the no-reserve case. Moreover, the simulations

with various parameter values of the biological and economic variables show that this relationship in the biomass always holds. In this section, we focus on the sensitivity analysis of the harvest by testing how the different values of transfer coefficient (m), harvest fraction (θ), harvesting cost (c) and size of negative shock (α) affect the results. Monte Carlo simulations generate 10,000 sets of 100-period time series of the harvest and we subsequently compute the difference in the average harvest over 100 periods between each policy scenario.

Transfer coefficient (m). The fish transfer coefficient is important in determining the benefit of marine reserves. Fish dispersal from the reserve to harvested populations depend on the transfer coefficient, m. The smaller the transfer coefficient, for example, the less the volume of fish that transfers from the reserve to harvested populations. As a result, the speed of stock recoveries as well as strength of smoothing the stock level over sites becomes low. Different values of the transfer coefficient are applied to test the effect of changes in the parameter.

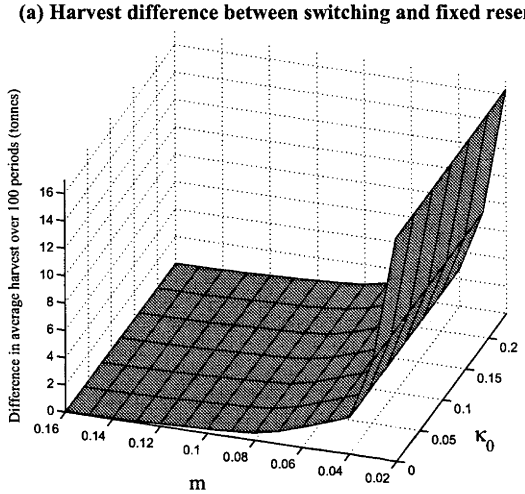
Panel (a) in Figure 3.4 presents the average harvest difference between the switching and fixed reserve cases. The harvest difference is always positive for all domains and the difference becomes larger as the linkages decreases. This result is consistent with what we saw in the density distribution of the harvest under the closed process (Figure 3.3). When there are only weak linkages between sites, the harvestable population in the fixed reserve case becomes much smaller than the switching strategy. In other words, as m increases, the sub-populations at sites 1 and 2 effectively become a single population so that rotating a reserve is not beneficial. In addition it is important to note that, in the switching strategy, the harvest remains at a high level through rotating the fishing area over time. However, the greater harvest produces a relatively smaller biomass than in the fixed reserve case.

Panel (b) in Figure 3.4 illustrates the difference in the average harvest between the switching and no-reserve cases. There is a clear negative relationship between the rate of fish transfer and harvest difference. Recall that the transfer coefficient, m, represents the proportion of the difference in biomass that migrates from a more dense to a less dense area. Panel (b) shows that if the migration rate is less than around 9 per cent, the no-reserve case is likely to produce a greater harvest than the switching strategy. In this case, there is no sufficient level of fish dispersal from the reserve to fishing ground. As a result, although the short-run harvest could be greater in the switching strategy following a large negative shock, the overall harvest becomes smaller than that in the fixed reserve case. On the other hand, once the migration rate becomes greater than about 9 per cent, the average harvest difference becomes greater. In this case, even if the harvest difference between the switching and no-reserve cases is negative at the steady-state, the short-run increase in the harvest of the switching strategy, following a large negative shock, can overwhelm the negative harvest difference at the steady-state. Consequently, the total harvest in the switching strategy becomes greater than in the no-reserve case. This is because the spillover from the reserve to harvested populations quickly smooths the average biomass over sites.

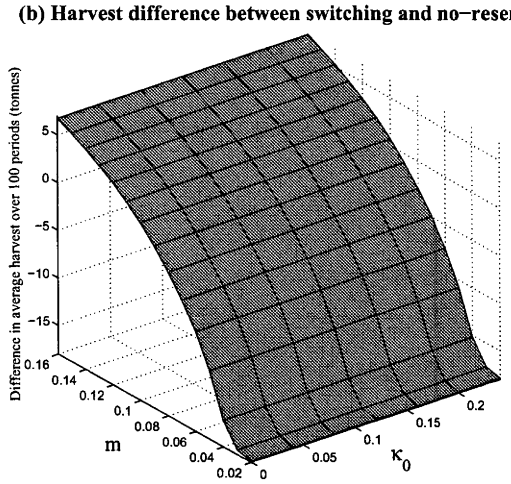
Panel (c) in Figure 3.4 shows the average harvest difference between the switching and fixed reserve case. The relationship between the transfer coefficient and harvest difference is similar to that in Panel (b). However, when the migration rate is relatively low, the difference in the average harvest is much lower than before. Without a sufficient level of fish migration from the reserve to harvested areas, fixing a non-fishing area at one site significantly decreases the total harvestable population, whereas the switching strategy avoids this by rotating the reserve over time.

Figure 3.4 **Sensitivity analysis of the harvest difference (transfer coefficient)**

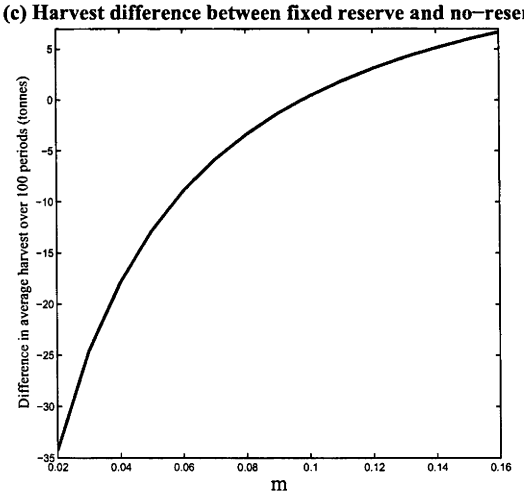
(a) Harvest difference between switching and fixed reserve



(b) Harvest difference between switching and no–reserve



(c) Harvest difference between fixed reserve and no–reserve



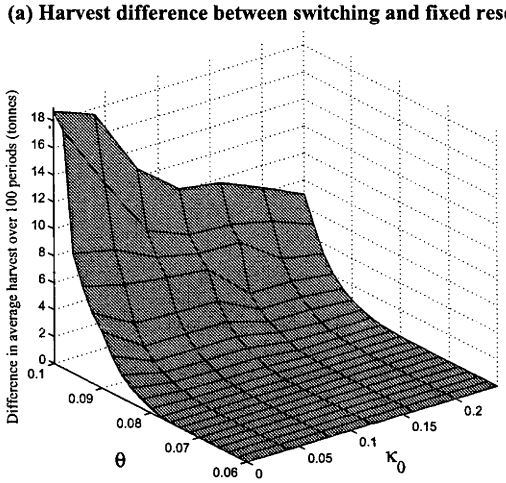
Harvest fraction (θ). The harvest fraction is another key variable to determine the difference between the three policy scenarios. If fish stocks are heavily exploited, the marginal benefit of fish migration from reserve to harvested areas increases. This is because the greater the harvest fraction, the larger the closed area is necessary to compensate for the greater reduction in biomass. Panel (b) in Figure 3.5 shows that the harvest difference monotonically increases as the harvest fraction increases. In contrast, when fish stocks are moderately exploited compared to the benchmark case, the average harvest in the no-reserve case can be greater than in the switching case. In this case, the marginal benefit of closing a fishing area is less than the foregone profit that could be obtained if the reserve were not created. A similar relationship in the average harvest difference between the fixed reserve and no-reserve cases is shown in Panel (c).

Where the average harvest difference between the switching and fixed reserve cases is compared in Panel (a) of Figure 3.5, there is a negative relationship between the size of the harvest fraction and the harvest difference. In the switching strategy, the fishing grounds are rotated to more profitable areas over time, producing a greater harvest, especially when the harvest fraction is large. However, switching the reserve also produces a relatively smaller biomass. Therefore, there are trade-offs between the harvest and biomass in switching a reserve. Also notice that the harvest difference diminishes as the transaction cost of switching increases. The optimal frequency of rotating a reserve approaches zero as the transaction cost rises. Once the transaction cost of switching reaches a certain level, the switching and fixed-reserve cases are identical.

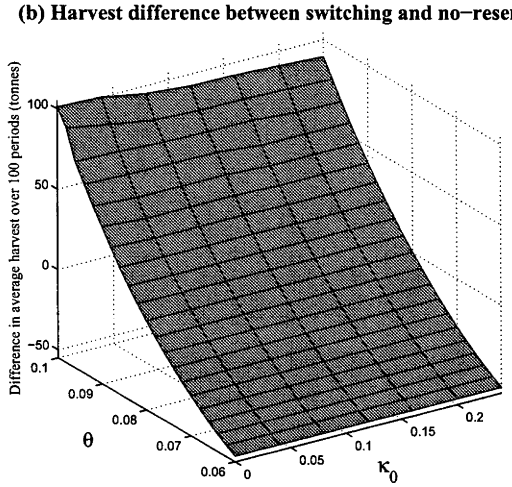
Harvesting cost (c). The optimal switching rule depends on the profitability of exploiting fish stocks and thus the price-cost ratio is an important factor in

Figure 3.5 **Sensitivity analysis of the harvest difference (harvest fraction)**

(a) Harvest difference between switching and fixed reserve



(b) Harvest difference between switching and no–reserve



(c) Harvest difference between fixed reserve and no–reserve

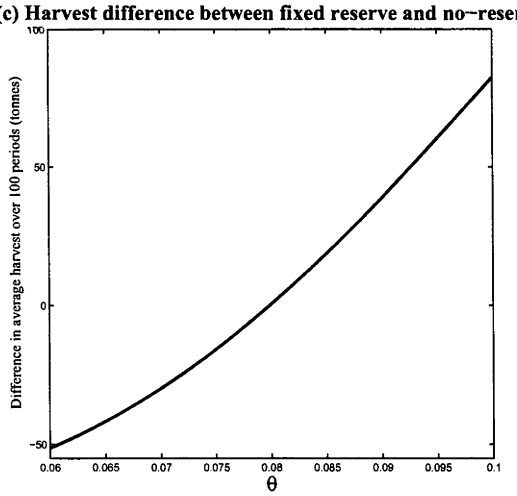
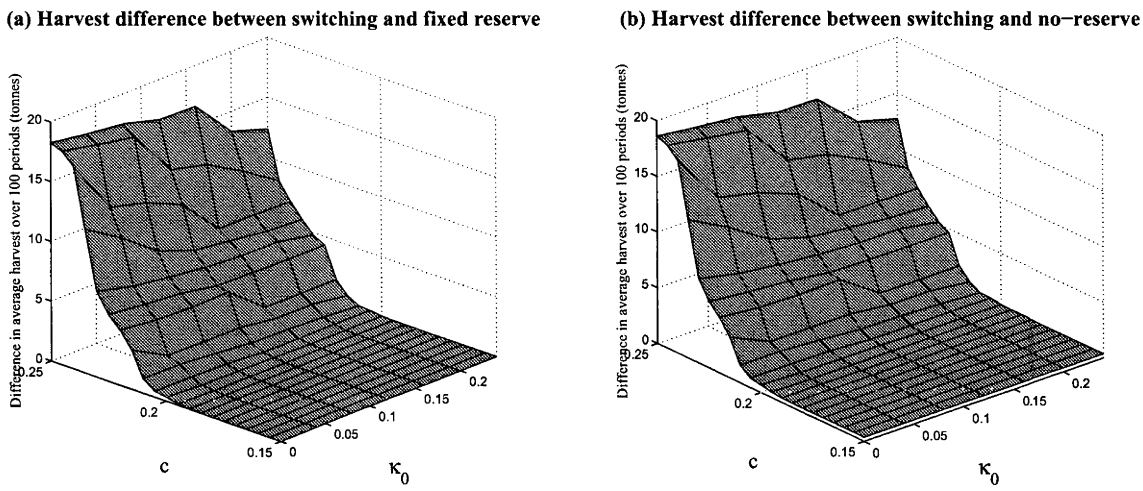


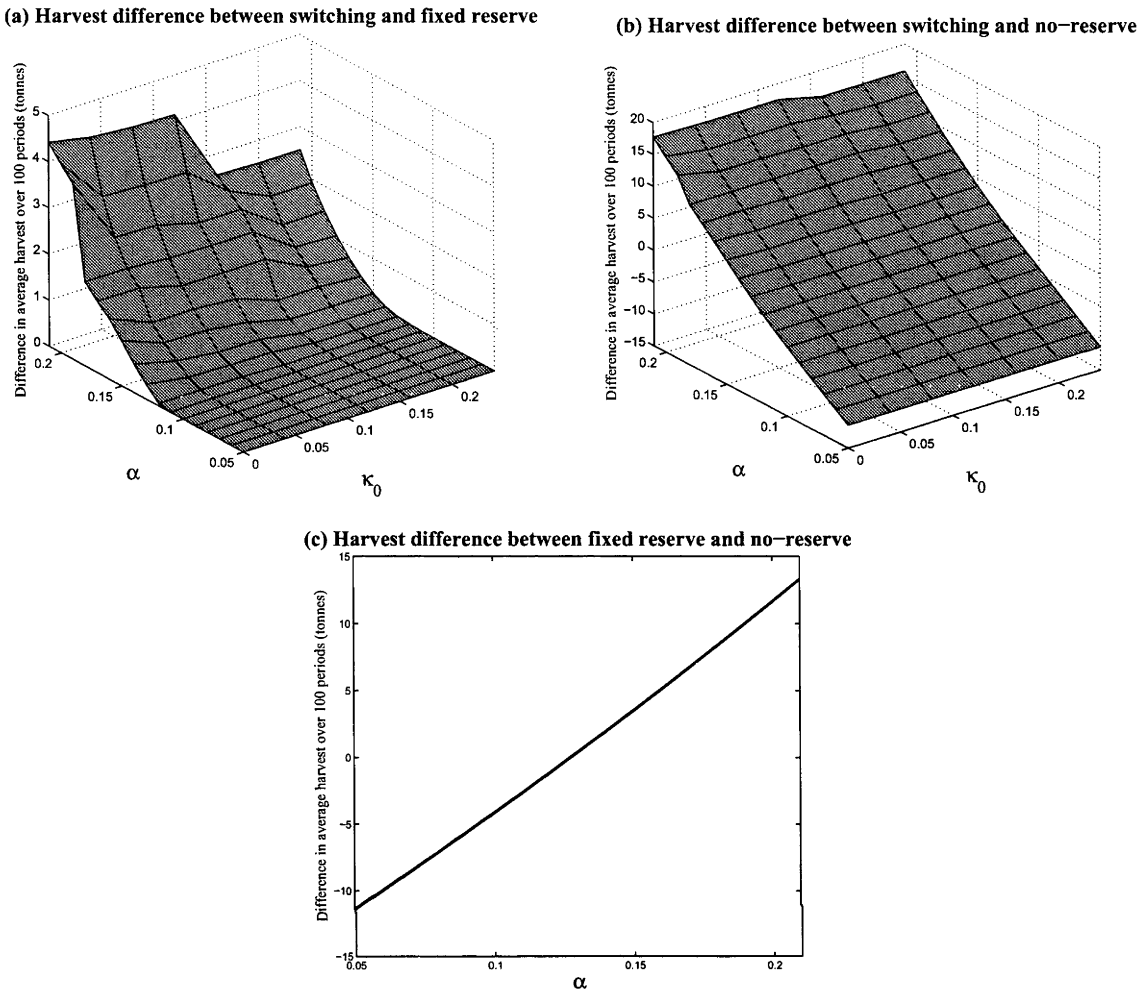
Figure 3.6 **Sensitivity analysis of the harvest difference (harvesting cost)**



effective fisheries management. Figure 3.6 illustrates how the harvest difference between the different policy scenarios changes in the harvesting cost. As the harvesting cost increases, for example, the net profit becomes more sensitive in a decline in the fish stock. As a result, the greater the harvesting cost the higher the frequency of rotating the fishing ground to a new site where fish stocks are relatively more abundant. This implies that, as the cost increases, the switching case has a greater harvest than the other two cases. It is important to note that there is an important linkage between this result and the optimal size of a reserve. Grafton et al. (2006b) find that the optimal reserve size increases in the harvesting cost. This is because a larger size of reserves is optimal with a greater cost of exploiting fish stocks, while generating a sufficient level of spillovers to fishing grounds.

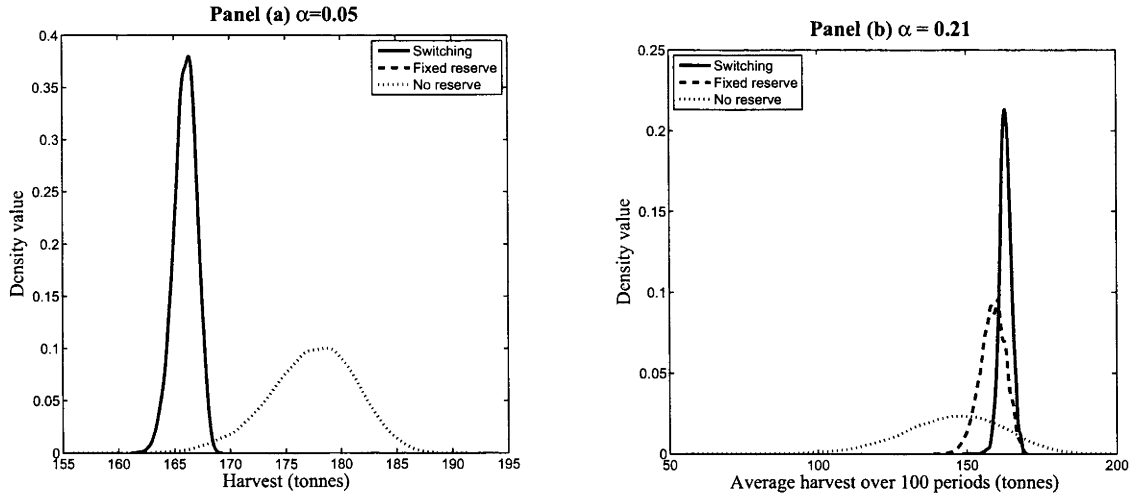
Size of negative shocks (α). An important function reserves possess is working as a buffer against a large negative shock in fish populations. Following a shock, fish dispersal from the reserve to harvested areas cause declined fish stocks recover to the steady-state level more quickly. This resilience effect is further enhanced in the size of shock and its arrival rate. Therefore, the cost of creating reserves also decreases as the size of shock and the arrival rate in-

Figure 3.7 **Sensitivity analysis of the harvest difference (size of negative shock)**



creases. These results are illustrated in Figure 3.7. Panels (b) and (c) of Figure 3.7 show that, when the size of shock is relatively small, the harvest difference between the management with and without reserves becomes negative. Panel (a) of Figure 3.8 also shows that, with a relatively small size of negative shocks ($\alpha = 0.05$), the mean value of the harvest in the management with reserves is smaller. In this case, although the reserve generates the spillovers to the harvested population, the benefit from the resilience effect is less than the cost of closing a fishing ground. On the other hand, reserves significantly increases the total harvest in the presence of relatively larger size of negative shocks (Panel (a) of Figure 3.7 and Panel (b) of Figure 3.8).

Figure 3.8 **Sensitivity analysis: density distribution of harvest**

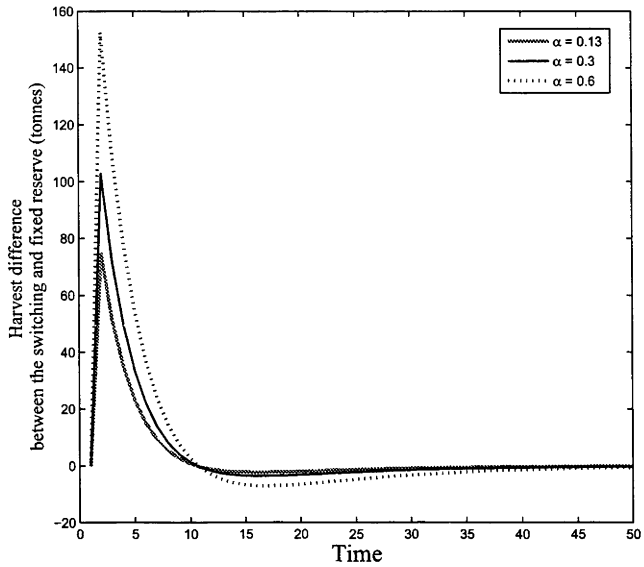


Switching and negative shock

The previous subsection shows that the economic benefit from switching a reserve is greater in the presence of large negative shocks. In other words, the switching and fixed reserve cases are identical when the size of shock is relatively small (see Panel (a) of Figures 3.7 and 8). As the size of shock increases, the harvest difference between the switching and fixed reserve cases becomes greater. Population density at the current fishing ground falls following a shock and then the area is closed for stock recovery in the switching strategy. In the meantime, the fishing ground is rotated to a more stock abundant area and, as a result, the harvest level increases following a large negative shock. We analyse this effect more carefully in Figure 3.9, which illustrates how the harvest difference between the switching and fixed reserve cases behaves over time following a large negative shock.[8] To test the sensitivity of the result, different sizes of negative shock are applied. In this simulation, a shock arrives at time one and the reserve is correspondingly rotated to a new area in the switching strategy, whereas the non-fishing area remains at the same place in the fixed reserve case.

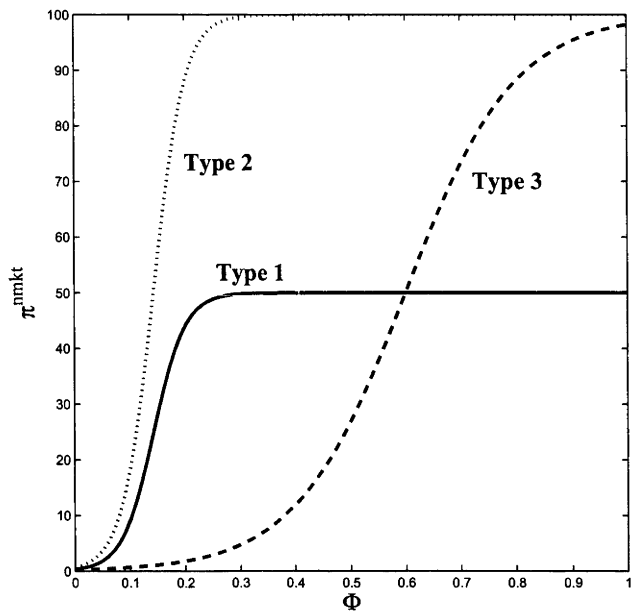
In the switching strategy, a fishing area is rotated to the previously closed area

Figure 3.9 **Response to different sizes of a negative shock: harvest difference between switching and fixed reserve**



where fish stocks are relatively more abundant, following the shock. As a result, the harvest difference between the switching and fixed reserve cases becomes much larger in the short run. At the same time, however, the greater harvest in the switching strategy results in a smaller biomass than the fixed reserve case. Therefore, the harvest difference also becomes negative for a certain period after the short-run jump. Particularly if the size of a shock is larger, then the short-run increase in the harvest of the switching strategy is greater; however the period will be longer for the harvest difference being negative after the short-run jump. The harvest difference eventually approaches zero as fish stocks recover to the steady-state level in the switching strategy. Overall, Figure 3.9 shows that there is a trade-off between the long-run and short-run harvest in rotating a reserve.

Figure 3.10 **Different types of the non-market value function**



Non-market value of reserves

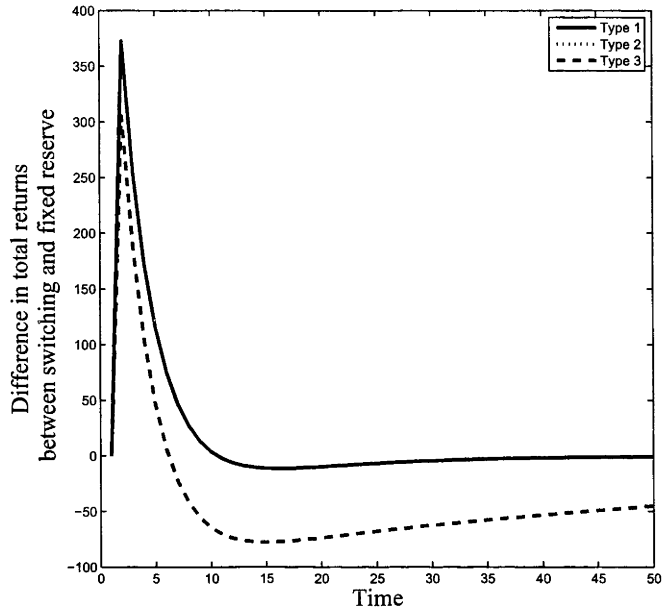
In this section we examine how the optimal switching rule changes once the non-market value of marine reserves is introduced. The regulator's objective is to maximise total returns (the sum of the discounted net profit and non-market value), instead of only the net profit of the fishery. To investigate how the optimal switching rule and its consequence differ depending on various characteristics of the non-market value of reserves, this paper considers three different types of the non-market value function illustrated in Figure 3.10. In Type 1, the non-market value of reserves reaches the maximum value in a relatively short time. In Type 2, the non-market value also rises to the maximum value relatively quickly, but the maximum value is greater than in Type 1. In Type 3, the maximum value is the same as Type 2, while it requires a higher biomass as well as longer closing period of a fishing area to realise the maximum value.

Total returns, switching and negative shock

Figure 3.11 shows how the difference in total returns between the switching and fixed reserve cases behaves over time following a large negative shock. A shock arrives at time one and the reserve is correspondingly rotated to a new site in the switching strategy, but the reserve remains at the same site as before in the fixed reserve case. As shown in Figure 3.9, switching the reserve increases the harvest in the short-run following the shock. This is because the fishing ground is rotated to the area where fish stocks are more abundant. The harvest in the switching strategy becomes greater than that in the fixed reserve case in the short-run, but the harvest difference also becomes negative for a certain period after the short-run jump due to the trade-off between the harvest and biomass in switching a reserve.

When the non-market value of reserves is included, however, switching the reserve also decreases the non-market value. This is because the non-fishing area is rotated to a new site and this produces a smaller biomass. If the non-market value of reserves rises to the maximum value in a relatively short time, such as in Types 1 and 2 in Figure 3.10, then the decrease in the non-market value quickly recovers to the maximum value. As a result, the time paths of the difference in total returns for Types 1 and 2 are almost the same in Figure 3.11. In contrast, if it requires a longer closing period and higher biomass to realise the maximum non-market value of reserves (Type 3 in Figure 3.10), the short-run jump becomes smaller than in the previous case. In addition, there is a much longer period that the difference in total returns between the switching and fixed reserve cases is negative after the short-run jump. Therefore, in this case, the overall benefit from switching is less than when the maximum non-market value of reserves is realised in a short time. In the next subsection, we analyse how the optimal frequency of switching relates this.

Figure 3.11 **Response to a negative shock: harvest difference between switching and fixed reserve**



Optimal frequency of switching

Table 3.1 shows the optimal frequency of switching in four different cases. Monte Carlo simulations generate 10,000 sets of time series of the control variable and the optimal frequency of switching is computed for each set of time series. When there is no non-market value of reserves, the non-fishing area is rotated for, on average, 3.53 per cent of the total period. The optimal frequency of switching is less, once the non-market value of reserves is included. This is because switching the reserve not only increases the harvest, but also decreases the total return in the presence of non-market values. The optimal frequency of switching also differs depending on the type of non-market value function. The optimal frequency is the highest with Type 1 and the lowest with Type 3. In Type 1, the maximum value is relatively low and is realised with a smaller biomass and shorter closing period. Thus, the forgone non-market benefit from rotating a reserve is less than the other two types. On the other hand, in Type 3, the maximum value is relatively high and a higher

Table 3.1 **Optimal frequency of switching** ($m = 0.1$, $\theta = 0.08$)

	Without non-market value	With non-market value		
		Type 1	Type2	Type3
Mean	0.0353	0.0198	0.0156	0.0139
Standard Deviation	0.0157	0.0111	0.0076	0.0063
Max	0.15	0.1	0.08	0.07
Min	0.1	0.01	0.01	0.01

Table 3.2 **Optimal frequency of switching** ($m = 0.1$, $\theta = 0.1$)

	Without non-market value	With non-market value		
		Type 1	Type2	Type3
Mean	0.363	0.275	0.182	0.108
Standard Deviation	0.0098	0.0127	0.0392	0.0063
Max	0.395	0.3	0.24	0.21
Min	0.32	0.11	0.04	0.01

biomass as well as longer closing period is required to realise the maximum value. Therefore, the foregone benefit from switching the reserve is greater than with the other two types. As a result, the optimal frequency of switching is less than the others.

In Table 3.1, the optimal frequency of switching is less, compared to the total time period. However, the frequency depends on the biological and economic parameters. As shown in the sensitivity analysis (Figures 3.4 to 3.9), the benefit of switching a reserve depends on these parameters. For example, Table 3.2 shows that when the harvest fraction is larger, the optimal frequency of switching increases for every case. We, however, emphasise that the relationship between each case still holds.

Concluding remarks

The use of marine reserves has received increased attention as a policy instrument to solve management failures in various fisheries. Previous studies have found that, under some conditions, reserves will provide a win-win solu-

tion, in which both biomass and harvest are greater than management without reserves. While these studies provide important insights into the design of optimal reserve management, much less is known about whether non-fishing areas should be rotated over time or whether they should be permanently fixed at an originally placed location.

Using a dynamic programming approach under uncertainty, this paper analyses a marine reserves switching strategy, with the non-market value of reserves in a stochastic environment. Applying the developed model to the red throat emperor fishery in the Great Barrier Reef, the study shows that the switching strategy can maintain a relatively high catch and biomass, even if there are weak linkages between sites. In contrast, if sufficient spillovers from the reserve to the harvested population were not generated, fixing the non-fishing area at one site could substantially decrease the total harvest. Therefore, when the migration rate is relatively low, there is a strong trade-off between the harvest and biomass in the fixed reserve case, whereas switching a reserve will decrease this trade-off. The paper also shows that, although the switching strategy produces a higher biomass than the no-reserve case, it has a relatively smaller biomass than when the reserve is permanently fixed at one site.

With respect to the non-market value of marine reserves, the results show that the optimal frequency of switching decreases once the non-market value is included in the decision process. Switching the reserve is, however, still optimal, if the non-market value is relatively low and if the value is realised with a relatively smaller biomass and shorter closing time. If the economic payoff from non-fishing activities is significantly large and/or if it is difficult to realise the non-market value (for example, higher biomass and longer closing period are required), switching the non-fishing area is then less likely to generate extra benefits. The paper also shows that the optimal timing of switching depends

on the size and arrival rate of large stochastic variations.

Overall, this study concludes that it is optimal to rotate a non-fishing area accordingly from one site to another, especially in the presence of large stochastic variations. The switching strategy could maintain high catch level as well as fish stocks. But, the fisheries environment and the condition of the ecosystem have to be carefully monitored to determine the timing of switching. A misplaced switching could increase the risk of environmental degradation as well as decrease the amenity value of reserves.

There are several potential extensions of this study. For instance, while in this chapter we employ a numerical technique to analyse the non-market value and optimal marine reserve switching strategies, it is worthwhile to develop a bioeconomic model that can be analytically solved. Such a model will help us to further understand the relationship between the non-market value and marine reserve switching. Another potential extension is to extend the current model to include an explicit spatial structure of marine reserves. The bioeconomic model constructed in this chapter only considers two sub-populations where the reserve and exploited populations are connected through the density dependent transfer function. By contrast, a spatially explicit bioeconomic model permits us to analyse how the optimal network structure of 'no-take' areas changes in different economic and biological conditions.

Appendix

Matlab code for marine reserve switching

```
%%%% switching.m
%%%%
%%%% This program solves a dynamic bioeconomic model
%%%% by collocation method
%%%% Policy instrument: marine reserve switching
%%%%

clear all
close all
clc

%%%%%%%%%%%%%%%%%%%%%%%%
% 1. SET MODEL PARAMETERES
%%%%%%%%%%%%%%%%%%%%%%%%

delta = 0.9; % discount rate
p = 5; % price para
c1 = 2; % cost para
c2 = c1; % cost para
r1 = .12; % int growth rate
r2 = .12; % int growth rate
K1 = 6913/2; % carrying capacity
K2 = 6913/2; % carrying capacity
K = K1+K2;

ep = inf; % price elasticity of demand
kap0 = 0.; % transaction cost
gam = 0.08; % harvest fraction
phi = 0.1; % fish movement para

% NON-MARKET VALUE FUNCTION
beta0 = 100;
beta1 = 5;
beta2 = 35;
beta3 = .5;

% INITIAL CONDITIONS
x10 = .5;
x20 = .5;
```

```
initarea = 1; % area initiall closed

x1min = 0; % min biomass in 1
x1max = K1; % max biomass in 1
x2min = 0; % min biomass in 2
x2max = K2 ; % max biomass in 2

% OTHER REQUIRED PARAMETERS
time = 200;
M = 10000;
tol = 1e-10; % tolerance
maxit = 10; % maximum number of iteration
n = 100; % collocation nodes
pol = 5; % degree of polynomial

% UNCERTAINTIES
uv = 10; % size of shock vector
us = 0.05; % size of uncertainty
un = linspace(0,1,uv); % discretise
zu = 1 + (2*un' - 1)*us;

d = ones(uv,1);
pi = 1/uv;
pim = d*pi;
pim = pim*d';
load indz_monte

% LARGE NEGATIVE SHOCK
% (TWO STATES 1:NO SHOCK ANA 2:SHOCK)
ssize = 0.13; % size of shock (percentage of fish stock)
pnsh = 0.04; % probability negative shock occur
nsh(1) = 1; % initially no shock
shtr = [1-pnsh pnsh; 1 0]; % transition matrix for shock
load nsh_monte

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% 2. COLLOCATION NODES and BASIS FUNCTION
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[z1,x1] = chebn(n,x1min,x1max); % nodes
[z2,x2] = chebn(n,x2min,x2max); % nodes

d1 = ones((n*n*2+n),1);
x1 = d1*x1';
```

```
x1 = x1(:);
x2 = x2*d1';
x2 = x2(:);

x = x1+x2;
save('x1','x1');
save('x2','x2');
save('x_aux','x')
clear x1 x2 d1

x = chebba2(x); % basis fn
save('x','x');
clear x

%%%%%%%%%%%%%%%%%%%%%%%%%%
% 3. COMPUTE NET PROFITS AT TIME 0
%%%%%%%%%%%%%%%%%%%%%%%%%%

load x1
load x2

nr = zeros((n*n*2+n)*n,2); % define
h1 = gam*x1;
h2 = gam*x2;
nr(:,1) = max(p*h2.^(1-1/ep) - c2*gam*K2,0); % when x1 is clsoe
nr(:,2) = max(p*h1.^(1-1/ep) - c1*gam*K1,0); % when x2 is clsoe
save('nr','nr');
clear nr x1 x2

% TRANSACTION COST
kap1 = kap0*(max(p*h1.^(1-1/ep) - c1*gam*K1,0));
kap2 = kap0*(max(p*h2.^(1-1/ep) - c2*gam*K2,0));
save('kap','kap1','kap2');
clear h1 h2 kap1 kap2

% NON-MARKET VALUE
load x_aux
d1 = ones(n,1);
t_aux = linspace(0,n*2,n*2+1);
t_aux = d1*t_aux;
t_aux = t_aux(:);
t = t_aux;
i = 0;
while i < n-1
t = [t;t_aux];
```

```
i = i+1;
end
clear t_aux d1

H = zeros((n*n*2+n)*n,2);

H(:,1)      =      alpha0*(alpha2*(x/K).*(1-x/K)+(1-alpha2)*(t/200).*(1-
t/200)).^alpha1;
H(:,2) = alpha0*(alpha2*(x/K).*(1-x/K)).^alpha1;
save('H','H');
clear b1 b2 H H1 H2 x x1 x1 t d d1

%%%%%%%%%%%%%%%%%%%%%%%
% 4. COMPUTE STATE TRANSITIONS
%%%%%%%%%%%%%%%%%%%%%%%

load x1
load x2

% WHEN X2 IS CLOSED
g11=zeros((n*n*2+n)*n,1);
g21=zeros((n*n*2+n)*n,1);

for i = 1:uv % take the expected value over uncertanty
g11 = g11 + pi*(min(x1 + zu(i)*r1*x1.*(1-x1/K1) +...
phi*K1*(x2/K2 - x1/K1),x1max));
g21 = g21 + pi*(min(x2 + zu(i)*r2*x2.*(1-x2/K2) -...
phi*K1*(x2/K2 - x1/K1)-gam*x2,x2max));
g21 = max((1-pnsh)*g21 + pnsh*(g21 - ssize*x2),0); % take the expected
value over negative shock
end

M11 = g11+g21;
save('M11','M11')
clear M11 g11 g21

% WHEN X2 IS CLOSED
g12=zeros((n*n*2+n)*n,1);
g22=zeros((n*n*2+n)*n,1);

for i = 1:uv % take the expected value over uncertanty
g12 = g12 + pi*(min(x1 + zu(i)*r1*x1.*(1-x1/K1) +...
phi*K1*(x2/K2 - x1/K1)-gam*x1,x1max));
g22 = g22 + pi*(min(x2 + zu(i)*r2*x2.*(1-x2/K2) -...
phi*K1*(x2/K2 - x1/K1),x2max));
```

```
g12 = max((1-pnsh)*g12 + pnsh*(g12 - ssize*x1),0); % take the expected
value over negative shock
end

M22 = g12+g22;
save('M22','M22')
clear M22 g12 g22

%%%%%%%%%%%%%%%%%%%%%%%%%%
% 5. GUESS INITIAL PARAMETERS (OLS)
%%%%%%%%%%%%%%%%%%%%%%%%%%

load nr load kap load H

% X1 IS CLOSED
nr_c1 = [nr(:,1)+H(:,1) nr(:,2)-kap2+H(:,2)];
nr_c1 = nr_c1';
[V1,G1] = max(nr_c1);

[g1 g2] = gfuncsfi(G1');
g = g1+g2;
clear g1 g2
g = chebba2(g);
a_c1 = g\V1'; %iniital guess for parameters
clear nr_c1 g V1 G1

% X2 IS CLOSED
nr_c2 = [nr(:,1)-kap1+H(:,2) nr(:,2)+H(:,1)];
nr_c2 = nr_c2';
[V2,G2] = max(nr_c2);

[g1 g2] = gfuncsfi(G2');
g = g1+g2;
clear g1 g2
g = chebba2(g);
a_c2 = g\V2'; %iniital guess for parameters
clear nr_c2 g V2 G2

% COMPUTE THE EXPECTED PAYOFFS
Ev = zeros((n*n*2+n)*n,2); %initial guess for v-fn

load M11
M1 = chebba2(M11);
save('M1','M1');
clear M11
```

```
Ev(:,1) = M1*a_c1;
clear M1

load M22
M2 = chebba2(M22);
save('M2','M2');
clear M22
Ev(:,2) = M2*a_c2;
clear M2

%%%%%%%%%%%%%%%%%%
% 6. MAIN LOOP
%%%%%%%%%%%%%%%%%%

it = 0;

while it<maxit

% WHEN X1 IS CLOSED
load nr
load kap
load H
nr_c1 = [nr(:,1)+H(:,1) nr(:,2)-kap2+H(:,2)];
clear nr kap1 kap2 H
[V1,G1] = max(nr_c1' + delta*Ev');
V1 = V1';
G1 = G1';
clear nr_c1

[g1 g2] = gfuncsfi(G1);
g = g1+g2;
clear g1 g2
g_c1 = chebba2(g);
clear g

aold_c1 = a_c1;
load x a_c1 = aold_c1 - (x-delta*g_c1)\(x*aold_c1-V1);
clear x g_c1

% WHEN X2 IS CLOSED
load nr
load kap
load H
nr_c2 = [nr(:,1)-kap1+H(:,2) nr(:,2)+H(:,1)];
clear nr kap1 kap2 H
```

```
[V2,G2] = max(nr_c2' + delta*Ev');
V2 = V2';
G2 = G2';
clear nr_c2

[g1 g2] = gfuncsfi(G2);
g = g1+g2;
clear g1 g2
g_c2 = chebba2(g);
clear g

aold_c2 = a_c2;
load x
a_c2 = aold_c2 - (x-delta*g_c2)\(x*aold_c2-V2);
clear x g_c2

% ERROR
error1 = max(abs(a_c1-aold_c1));
error2 = max(abs(a_c2-aold_c2));
if error1 < tol
ind = 1;
break
end
aux(it+1) = error1;

figure
hold on
plot(it,error1,'o',it, error2,'+')
xlim([1,it+2])
hold off

load M1
Ev(:,1) = M1*a_c1;
clear M1
load M2
Ev(:,2) = M2*a_c2;
clear M2

it = it+1;

end

%%%%%%%%%%%%%%%%%%
% 7. SIMULATION
%%%%%%%%%%%%%%%%%%
```

```
x1t = zeros(time+1,M);
x2t = zeros(time+1,M);
xt = zeros(time,M);
h1t = zeros(time,M);
h2t = zeros(time,M);
ht = zeros(time,M);
nrt = zeros(time,M);
Tt = zeros(time,M);
ind1 = zeros(time,M);
ind2 = zeros(time,M);
ind3 = zeros(time,M);
ind4 = zeros(time,M);
ind5 = zeros(time,M);
ind6 = zeros(time,M);
Ht = zeros(time,M);
tt = zeros(time+1,M);

x1t(1,:) = K1*x10; % initial condition
x2t(1,:) = K2*x20;
t = linspace(0,n,n+1)';
tt(1,:) = 0;

[z1,x1] = chebn(n,x1min,x1max); % nodes
[z2,x2] = chebn(n,x2min,x2max); % nodes

G1 = reshape(G1,n,(n*n*2+n));
G2 = reshape(G2,n,(n*n*2+n));

% AREA INITIALLY CLOSED
if initarea == 1
state = 1;
ind4(1,:) = 1;
elseif initarea == 2
state = 2;
ind4(1,:) = 2;
end
clear Ev V1 V2 b d1 pim z1 z2

for j = 1:M

for i = 1:time

[aux,ind1(i,j)] = min(x1<x1t(i,j));
[aux,ind2(i,j)] = min(x2<x2t(i,j));
```

```
if x1t(i,j) >= max(x1)
ind1(i,j) = n;
end

if x2t(i,j) >= max(x2)
ind2(i,j) = n;
end

if state == 1
ind4(i+1,j) = G1(ind2(i,j),(ind1(i,j)-1)*n+ind3(i,j));
elseif state == 2
ind4(i+1,j) = G2(ind2(i,j),(ind1(i,j)-1)*n+ind3(i,j));
end

if state == 1

h2t(i,j) = gam*x2t(i,j);
ht(i,j) = h2t(i,j);
nrt(i,j) = p*ht(i,j)^(1-1/ep) -c2*gam*K2;

if nrt(i,j) <= 0 nrt(i,j) = 0;
ht(i,j) = ((c2*gam*K2)/p)^(1/(1-1/ep));
end

x1t(i+1,j) = min(x1t(i,j) + zu(indz(i,j))*r1*x1t(i,j)*(1-x1t(i,j)/K1)
+...
phi*K1*(x2t(i,j)/K2 - x1t(i,j)/K1),K1);
x2t(i+1,j) = min(x2t(i,j) + zu(indz(i,j))*r2*x2t(i,j)*(1-x2t(i,j)/K2) -...
phi*K1*(x2t(i,j)/K2 - x1t(i,j)/K1) -... gam*x2t(i,j) + (1-
nsh(i,j))*x2t(i,j)*ssize,K2);
Tt(i,1) = phi*K1*(x2t(i,j)/K2 - x1t(i,j)/K1);
xt(i,j) = x1t(i,j) + x2t(i,j);

elseif state == 2
h1t(i,j) = gam*x1t(i,j);
ht(i,j) = h1t(i,j);
nrt(i,j) = p*ht(i,j)^(1-1/ep) -c1*gam*K1;

if nrt(i,j) <= 0
nrt(i,j) = 0;
ht(i,j) = ((c2*gam*K2)/p)^(1/(1-1/ep));
end

x1t(i+1,j) = min(x1t(i,j) + zu(indz(i,j))*r1*x1t(i,j)*(1-x1t(i,j)/K1)
```

```
+...
phi*K1*(x2t(i,j)/K2 - x1t(i,j)/K1) -...
gam*x1t(i,j) + (1-nsh(i,j))*x1t(i,j)*ssize,K1);
x2t(i+1,j) = min(x2t(i,j) + zu(indz(i,j))*r2*x2t(i,j)*(1-x2t(i,j)/K2) -...
phi*K1*(x2t(i,j)/K2 - x1t(i,j)/K1),K2);
Tt(i,1) = phi*K1*(x2t(i,j)/K2 - x1t(i,j)/K1);
xt(i,j) = x1t(i,j) + x2t(i,j);

end

if ind4(i+1,j) ~= ind4(i,j)

tt(i+1,j) = 0;

if ind4(i+1,j) == 1
kap = kap0*(p*h1t(i,j)^(1-1/ep)-c1*gam*K1);
elseif ind4(i+1,j) == 2
kap = kap0*(p*h2t(i,j)^(1-1/ep)-c2*gam*K2);
end
nrt(i,j) = nrt(i,j) - kap;

elseif ind4(i+1,j) == ind4(i,j)

tt(i+1,j) = min(tt(i,j)+1,200);
nrt(i,j) = nrt(i,j);

end

if ind4(i+1,j) == 1
state = 1;
elseif ind4(i+1,j) == 2
state = 2;
end

end

end
```

Endnotes

[1] There is a large number of previous studies on marine reserves. Comprehensive literature reviews are provided by for example Guénette et al. (1998), Hilborn et al. (2004) and Grafton et al. (2005).

[2] There are few but important previous studies looking at temporary fishing closures. For example see Hilborn and Walters (1992), Guénette et al.(1998) and Costello and Polasky (2008). Not on marine reserves but Costello and Polasky (2004) also study the dynamic site selection problem on protecting biodiversity.

[3] A similar specification is utilized in a recent study on fishery profits of marine reserves (White et al. 2008). An alternative specification of the harvest function is to make θ a control variable so that the level of harvest is optimally controled over time. However, this will increase the computational burden.

[4] See Judd (1998) and Miranda and Fackler (2002) for the technical details.

[5] Leigh et al. (2006) estimated that the exploitable biomass fell to approximately 60 per cent in the late 1990s.

[6] See Appendix for Matlab code.

[7] In a deterministic environment the biomass at the maximum sustainable yield (MSY) at site i is $B^i_{MSY} = \frac{(r-m)K^i}{2r}$. With the given parameter values $B^i_{MSY} = 288.04$ and $MSY = 31.68$.

[8]The difference between the fixed reserve and no-reserve cases, in which the harvest is optimally controlled, is shown in Grafton et al. (2006b).

Chapter 4

Connectivity and network structure of marine reserves

Introduction

Terrestrial and marine landscapes are typically heterogeneous. The spatial characteristics of the biological system and connectivity between adjacent sites are fundamental factors in natural resource management (Wilen 2007). An important issue is how to implement an ecologically and economically effective control of resource use, while taking into account the different diffusion process and spatial heterogeneity in the management area. In fisheries management, one widely recognised spatially explicit strategy is the use of marine reserves, which typically restricts resource development and fishing activities in protected areas. In the past two decades a number of studies have addressed the ecological and economic impact of creating a reserve. In this paper we develop a spatial bioeconomic model to address issues of marine reserve design in the presence of a large negative shock in fish stocks.

One of the most important insights from previous studies is that, in various cases, the use of reserves will provide a win-win situation in which the ecosystem and economic payoffs are both improved (Grafton et al. 2006b; Sanchirico et al. 2006; Worm et al. 2006; White et al. 2008). However, whether marine reserve management is implemented in an effective way and produces expected policy outcomes largely depends on the design of marine reserves. A misplaced reserve increases the cost of management and will not achieve a desirable outcome (Sala et al. 2002; Botsford et al. 2003; Gerber et al. 2003; Roberts et al. 2003; Balmford et al. 2004). Another important insight from previous studies is that marine reserves work particularly well in the presence of large variations in the marine environment (Lauck et al. 1998; Grafton et al. 2006b; Costello & Polasky 2008). Creating a non-fishing area hedges against uncertainty in the ecosystem and maintains biodiversity as well as fisheries.

Using a stochastic dynamic optimisation framework, we focus on the connectivity and network structure of marine reserves in regulated fisheries. The linkage between different sites is crucial to determining the effectiveness of reserves management. Roberts (1997) and Shanks et al. (2003), for example, show that reserves need to be established close enough together to effectively maintain biodiversity. This is especially the case when the fish dispersal process is passive such as in coral reefs. Reserves that are close guarantee the successful movement of larvae and spawning biomass and also enhance biodiversity conservation.

In addition, because neighbouring fisheries benefit from reserves, biological as well as economic connectivity between neighbouring sites is a crucial factor in determining the benefit from creating a reserve (Roberts et al. 2001). The use of reserves is economically optimal if and only if the dispersal benefit from protected areas is greater than the cost of reduction in fishing waters.

Connectivity between adjacent sites is determined by different factors, such as, the nature of fish dispersal, spatial heterogeneity in the economic and biological characteristics as well as the presence of stochastic variation and input/effort distribution (Sanchirico & Wilen 2001; Smith & Wilen 2003; Grafton et al. 2006b; Sanchirico et al. 2006; Costello & Polasky 2008).

A study that shares a similar motivation to this study is Sanchirico (2005). He analyses how different assumptions about the connectivity between two discrete spaces influences the benefit from closing a fishing ground in open access fisheries. Considering three different properties of biological production, he illustrates the parameter regions where creating a reserve yields a win-win situation. Similar to his study, this paper also employs a discrete space model. Our study is different from Sanchirico (2005) in that we use a metapopulation model with four discrete patches and investigate not only the connectivity but also policy outcomes with different network structures of reserves.

Although most bioeconomic models in previous studies restrict the spatial dimension within two discrete patches, partly due to the model tractability, a two-patch (reserve-fishing ground) model cannot deal with the spatial structure of marine reserves. In this paper, we develop a bioeconomic model with four discrete patches, incorporating a feedback approximation method developed by Sirakaya et al. (2006). Using the model we investigate the following research questions: to what extent do the direct/indirect linkages between reserves and fishing grounds matter for policy outcomes of marine reserves; how does the buffering effect of reserves change in different network structures of reserves; and to what extent does the spatial heterogeneity in biological and economic parameters affect the nature of fish migration across adjacent sites.

Another difference between Sanchirico (2005) and this study is that, instead of open access, we consider a fishery where the level of harvest is optimally

controlled over time. It is important to know to what extent the connectivity and network structure of reserves affect policy outcomes in regulated fisheries. Creating a non-fishing area itself does not solve the common-pool resource problem. Thus, the use of reserves is not a panacea for every management failure (Allison et al. 1998; Hilborn et al. 2004) and, in open access fisheries, reserves would not provide a win-win situation in many instances (Hannesson 2002). Controlling fishers' behaviour and incentives is a key for successful fisheries management (Grafton et al. 2006a).

The rest of the paper is organised as follows. In Section 4.2 we develop a spatial bioeconomic model of marine reserves. The computational strategy to simulate the model is also discussed. The parameter values for the model simulations are extracted from a previous study, Grafton et al. (2006b), in the Pacific halibut fishery, which is described in Section 4.3. In Section 4.4 we simulate the economic and biological outcomes of marine reserves under different network structures as well as different assumptions about the spatial heterogeneity. Section 4.5 provides concluding remarks.

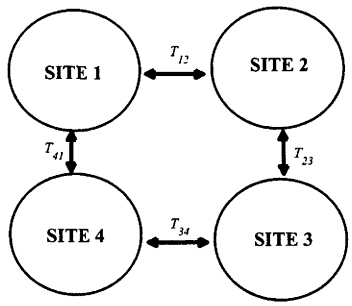
The model

Population dynamics

The paper employs a metapopulation model with four sites, in which each site represents a discrete space (Figure 4.1). The linkages between adjacent sites are modelled by the transfer function $T_{ij}(x_t^i,\ x_t^j)$, which captures the fish transfer from one site to another. Here, x^i and x^j denote the fish stock in sites i and j and $i,\ j \in \mathcal{N} = (1, 2, 3, 4)$.

Time is discrete, indexed by $t \in \mathbb{N}$. The population dynamics in site i with its

Figure 4.1 **Model image**



adjacent sites j at time t are modelled as:

$$x^i_{t+1} = x^i_t - h^i_t + z^g_t r^i x^i_t\Big(1 - \frac{x^i_t}{K^i}\Big) + \sum_j^{j\neq i} T_{ij}(\mathbf{x}) - S\left(x^i_t,\ x^j_t,\ z^s_t\right), \text{ if site } i \text{ is open; and}$$

$$x^i_{t+1} = x^i_t + z^g_t r^i x^i_t\Big(1 - \frac{x^i_t}{K^i}\Big) + \sum_j^{j\neq i} T_{ij}(\mathbf{x}) - S\left(x^i,\ x^j_t,\ z^s_t\right), \text{ if site } i \text{ is closed} \tag{4.1}$$

where x^i_t is the fish stock and K^i is the carrying capacity in site i. The first term is the fish escapement in each period. If site i is a fishing ground, the fish stock is exploited by the harvest level $h^i_t > 0$, while $h^i_t = 0$ if a reserve is established on the site. The second term is the density dependent growth function with site specific intrinsic growth rate, r^i and z^g_t represents stochastic variation in fish growth at site i. The growth uncertainty is specified as $z^g = 1 + (2u - 1)\epsilon$, where u is a uniformly discretised grid. The term ϵ determines the size of variations and lies between 0 and 1, indicating from 0 per cent to 100 per cent variation (Sethi et al. 2005). It is assumed that z^g follows a Markov process with the same transition probabilities between each state. The third term, $\sum_{j,\ i\neq j} T_{ij}(\cdot)$, is the net fish flow between neighbouring sites i and j. The last term $S(\cdot)$ is a negative shock function.

Transfer function

The transfer function captures different forms of connectivity between adjacent sites. This term thus represents the fish dispersal pattern and the volume of fish flow from one site to another. Assume that the fish flow depends on the relative population density between adjacent sites. The density dependent dispersal process is a common specification in bioeconomic modelling (for example, Conrad 1999; Sanchirico & Wilen 2001; Grafton et al. 2006b). Here, we specify the transfer function as:

$$T_{ij}(\mathbf{x}) = m^{ij}K^i\left(\frac{x^j}{K^j} - \frac{x^i}{K^i}\right) \quad \text{if } i \text{ and } j \text{ are adjacent,} \tag{4.2}$$

where m^{ij} is the transfer coefficient for connecting sites i and j. We assume that the carrying capacity in each site is the same and then the transfer function becomes $m^{ij}\left(x^j - x^i\right)$ where m^{ij} is the fraction of the difference in the population density between sites i and j.

Negative shock

The marine environment faces different types of large negative shocks. For example, the use of fishing gear, such as bottom trawling, increases the risk of environmental degradation. Rising and more volatile sea temperatures, due to climate change, also increases the uncertainty in fisheries management. In this paper the negative shock function, $S(\cdot)$, captures different forms of a large negative shock in the fish population. The function is specified as:

$$S(x_t^i,\ x_t^j,\ z_t^s) = \begin{cases} \alpha_t^i x_t^i & \text{for } t \in [t^*,\ \tau] \\ 0 & \text{for } t \notin [t^*,\ \tau] \end{cases} \tag{4.3}$$

where we assume that the size of a negative shock is proportional to the stock level that is determined by parameters α_t^i at time t. A negative shock arrives

at time t^* and persists until time τ . We assume that $1 > \alpha_{t^*} > \alpha_{t^*+1} > \cdots > \alpha_{\tau-1} > \alpha_\tau > 0$, hence the size of shocks diminishes over time and eventually vanishes.

In this paper we consider two scenarios of negative shocks: negative shocks are realised only in the harvested population; and shocks are realised in both the reserve and harvested populations. We define $\Psi \subseteq \mathcal{N}$ as a set of the sites that are open for fishing. Then, for the first scenario, the specification of the shock function is $S(\cdot) = \alpha_t^i x_t^i,\ i \in \Psi$ and, for the second scenario, $S(\cdot) = \alpha_t^i x_t^i,\ i \in \mathcal{N}$.

Dynamic optimisation model

Suppose that the regulator aims to maximise the discounted net profit from fishing over an infinite time horizon. The regulator's control variable is a total catch limit in each fishing ground. Then, the net profit function at time t is specified as:

$$\pi_t = p(h_t)h_t - \sum_{i \in \Psi} c(x_t^i)h_t^i, \tag{4.4}$$

where $h = \sum_{i \in \Psi} h^i$ is the total harvest. The term $p(\cdot)$ is the inverse demand function and $c(\cdot)$ is the cost function. We define the inverse demand and cost functions as:

$$p(\cdot) = \bar{p} h_t^{-1/\delta} \text{ and } c(\cdot) = \bar{c}^{\,i}/x_t^i \tag{4.5}$$

where δ is the constant price elasticity of demand and $\bar{p}$ and $\bar{c}^i$ are the parameters. Note that if the elasticity is positive ($0 < \delta < \infty$), then the demand curve is downward sloping ($p_h < 0$), while the demand curve is horizontal if $\delta \to \infty$. Hence, this demand form can capture the different types of demand. Also note that $c_x < 0$ and $c_{xx} > 0$. In other words, the harvesting cost decreases in the abundance of fish and the decreasing rate is progressive.

Combining the model developed above, the regulator's objective function and

constraints are:

$$J = \max \mathbb{E} \sum_{t=0}^{\infty} \beta^t \pi_t \tag{4.6}$$

$$\text{subject to} \begin{cases} \text{if site } i \text{ is open;} \\ x_{t+1}^i = x_t^i + z_t^{gi} r^i x_t^i \left(1 - \frac{x_t^i}{K^i}\right) + \sum_j^{j \neq i} T_{ij}(\mathbf{x}) - S\left(x_t^i,\ x_t^j,\ z_t^s\right) - h_t^i \\ \text{if site } i \text{ is closed;} \\ x_{t+1}^i = x_t^i + z_t^{gi} r^i x_t^i \left(1 - \frac{x_t^i}{K^i}\right) + \sum_j^{j \neq i} T_{ij}(\mathbf{x}) - S\left(x_t^i,\ x_t^j,\ z_t^s\right) \\ x_0^i = x^i(0),\quad z_0^{gi} = z^{gi}(0)\quad z_0^s = z^s(0) \text{and } i = 1,2,3,4 \end{cases} \tag{4.7}$$

where $\mathbb{E}$ is the mathematical expectation operator, β is a discounting factor and J is the sum of the expected discounted net profit. Therefore, the regulator maximises the sum of the expected discounted net profit from fishing and is subject to the population dynamics in both the reserve and harvested populations. Also, initial conditions for the state variables are given.

Simulation strategy

Using Matlab and its Genetic Algorithm and Direct Search toolbox we simulate the developed model.[1] In this model there are six state variables, x^i, $i = 1, \ldots, 4$, z^g and z^s. Thus, the traditional direct and indirect numerical approaches, such as discretisation and projection methods, are not applicable due to the curse of dimensionality problem. We alternatively adopt a simulation method developed by Sirakaya et al. (2006). In their approach, a feedback policy function, $h^i = \Phi(\Gamma_t,\ \Omega)$, is parameterised by a neural network where Γ_t is the vector of the input variables at time t and Ω is the vector of connection and bias weights of the neural network, respectively. Neural networks are flexible non-linear function forms to approximate unknown functions.[2] The function consists of single or multiple layers of networks that connect the output and inputs. This paper employs the following feedforward network with a

logistic function:

$$\begin{aligned}
\Phi(\Gamma_t,\ \Omega) &= \frac{\gamma_{min} + (\gamma_{max} - \gamma_{min})}{1 + exp(-\Gamma_t^2)} \\
\Gamma_t^2 &= \omega_1^2\Gamma_{1t}^1 + \omega_2^2\Gamma_{2t}^1 + \omega_3^2\Gamma_{3t}^1 + \omega_4^2\Gamma_{4t}^1 + \omega_5^2\Gamma_{5t}^1 + \omega_6^2\Gamma_{6t}^1 + v^2 \quad (4.8) \\
\Gamma_{it}^1 &= \frac{1}{1 + exp(-\omega_i^1\Gamma_{it}^0 + v_i^1)} \\
\Gamma_{it}^0 &= (x_t^1,\ \ldots x_t^4,\ z_t^g,\ z_t^s)
\end{aligned}$$

With this specification, the output, Φ, is bounded between γ_{min} and γ_{max}, where $\gamma_{min} = 0$ and $\gamma_{max} = K^i$ since here the output is the harvest in site i. Given a different set of initial conditions for the state variables, $\Gamma_{i0}^0 \in \Gamma(0) = (x_0^1,\ \ldots x_0^4,\ z_0^g,\ z_0^s)$, the sum of the discounted net profit is computed. The connection and weights are trained through an iteration procedure to maximise the sum of the discounted net profit.

The underlying logic of this algorithm is that if the trained feedback policy rule maximises the sum of the discounted net profit, it must also maximise the profit over a range of initial conditions. Thus, the objective function in the optimisation problem becomes

$$\tilde{J} = \sum_{\Gamma_{i0}^0 \in \Gamma(0)} \sum_{t=0}^{T} \beta^t \pi_t \qquad (4.9)$$

To approximate the optimal feedback rule we employ a genetic algorithm.[3] The genetic algorithm is a stochastic search optimisation method that is motivated from the evolution process in biology, while incorporating genetic concepts, such as, *chromosome, generation, mutation* and *crossover.* We first construct a fixed-size population, $Y = (y_1, \ldots, y_M)$, where $y_m,\ m = 1, \ldots, M$, is called individual (or *chromosome*) in the population. The objective function is evaluated by each individual. The larger the size of the population, the wider the domain to be searched for the optimal feedback policy rule. The policy rule

is then trained through an iteration procedure, called *generation.* In each iteration individuals producing higher values of the objective function are likely to be selected to produce new individuals for the next generation. The new generation consists of three types of children, *elite, crossover* and *mutation.*

Elite children are the individuals who have the highest values of the objective function in the current generation. They survive to the next generation. In the *crossover* process, those y_m with higher values of the objective function are selected to reproduce individuals for the next generation. There are practically infinite ways to reproduce children in this step. In this paper we draw a random binary vector and the children are created correspondingly. In the *mutation* process, an old individual, y_m, is replaced by an alternative individual through a random draw from a Gaussian distribution. This guarantees a wide range of searching domains and avoids convergence in a local optima. Through the iterative reproduction procedure, those individuals with higher values of the objective function survive but weaker ones vanish.

Pacific halibut fishery

The model developed in the previous section is applied to the Pacific halibut fishery in the North Pacific Ocean. Pacific halibut (*Hippoglossus stenolepis*) is a longlived large flatfish and the halibut fishery has been one of the most important and valuable fisheries for the last 120 years in the region. The commercial halibut fishery is mainly conducted in Alaska, British Columbia and the North West Pacific, engaged in by Canada and the United States. The major fishing gear is a long-line (Herrmann 1996).

Since 1923 the fishery has been overseen by the International Pacific Halibut Commission (IPHC: originally named International Fisheries Commis-

sion), conducting stock assessment as well as providing scientific reports and recommending measures to manage and protect the industry. Similar to the experience in other modern fisheries, as the fishing capacity improved and the market expanded, new entrants were attracted to the fishery and the 'race-to-fish' was expeditiously induced (Wilen & Homans 1998). The fishing season had, consequently, been reduced to very short periods, especially from the mid 1970s to the mid 1990s. For example, a fishing ground in Alaska was open for only two days in 1994. Given this regulated open-access problem (Homans & Wilen 1997), the Canadian Department of Fisheries and Oceans (DFO) implemented an individual vessel quota (IVQ) program in the British Columbia halibut fishery in 1991. The North Pacific Fisheries Management Council (NPMFC) also introduced an individual fishery quota (IFQ) program for Alaskan fishery in 1995. After implementation of the policy, the fishing season in Alaska is stable at 245 days (Herrmann & Criddle 2006)

The economic payoffs from establishing a reserve in the fishery is analysed in Grafton et al. (2006b). The parameter values for the biological and economic variables for the model developed in the previous section are extracted from their study. The intrinsic growth rate r is 0.2985 and the carrying capacity K is 0.9631 million pounds. The parameter, $\bar{p}$, in the inverse demand function is 0.07 and the price elasticity of demand is 1.23. In the absence of adequate data, the cost parameter $\bar{c}$ is set at 0.03 and the transfer coefficient $m = 0.1$. The variation in the growth uncertainty is described by $\epsilon = 0.15$ and the time discounting rate is 5 per cent.

Simulation Results

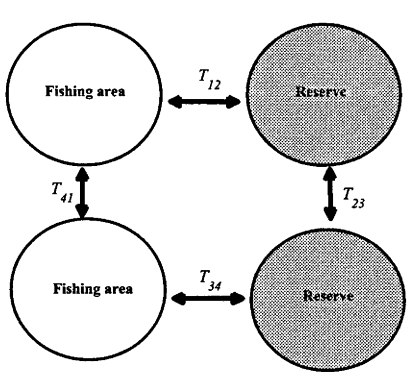
Network structures, negative shocks and connectivity

In this section we consider the two different network structures of marine reserves (Figure 4.2) and their policy outcomes. In the first structure, a reserve is directly connected with the other reserve and also with a fishing area, but, in the second structure, one reserve and the other reserve are only indirectly connected through a fishing area. In other words, each reserve and fishing area is more closely linked in Structure 2. Comparing these two network structures allows us to investigate to what extent policy outcomes of marine reserves vary in the direct and indirect linkage between the reserve and harvested populations.

When negative shocks are only realised in fishing grounds. Figure 4.3 illustrates the net profit from fishing and the total biomass over time under the two network structures. Three large negative shocks are introduced at times 30, 55 and 80 and the size of the shocks are $\alpha_{30} = 0.08$, $\alpha_{55} = 0.12$ and $\alpha_{80} = 0.16$, respectively. Different values of α are applied here so that the sensitivity of the results is analysed. In Figure 4.3, the shocks are only realised

Figure 4.2 **Network structures**

2.1 Structure 1



2.2 Structure 2

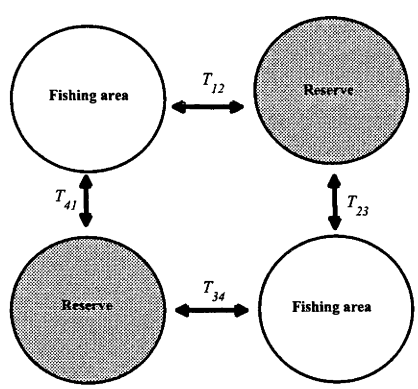
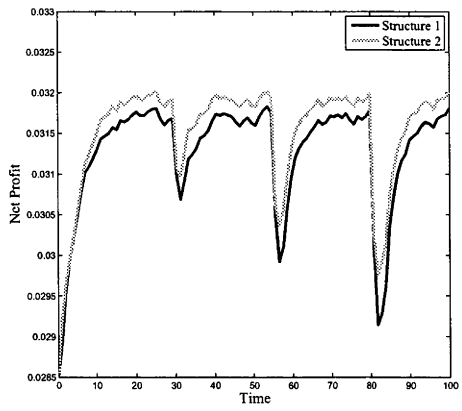
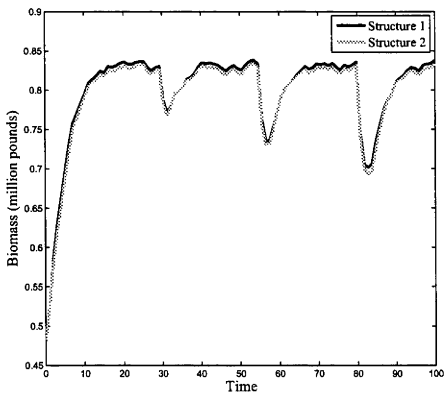


Figure 4.3 **Net profit and biomass over time**
(negative shocks are realised only in the fishing areas)

4.3.1 Net profit



4.3.2 Total biomass



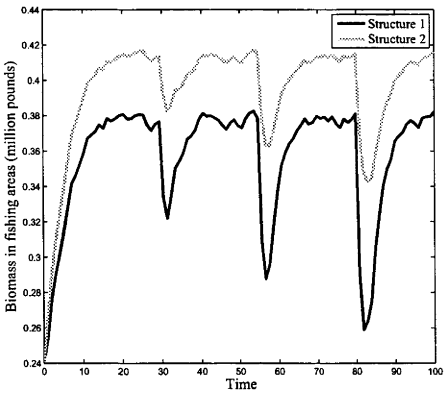
in fishing grounds and not in reserves. Hence, this is a case in which a major risk for environmental degradation is due to site-specific events such as fishing activities.

The figure shows that when the reserve has a stronger connectivity with the harvested population (Structure 2), the net profit is greater both at the steady state and following negative shocks. The difference in the total biomass between the two structures is, on the other hand, not substantial. Also, the larger the size of the shock, the greater the difference in the net profit following the shocks between Structures 1 and 2. This is because the closer linkage between the reserve and harvested populations enhances the buffering effect associated with the economic efficiency against the impact of negative shocks. In other words, since the fishing ground in Structure 2 is more closely and directly connected with the reserve than that in Structure 1, the population density across different sites is smoothed through the fish dispersal faster. The total profit in Structure 2 is consequently greater than that in Structure 1.

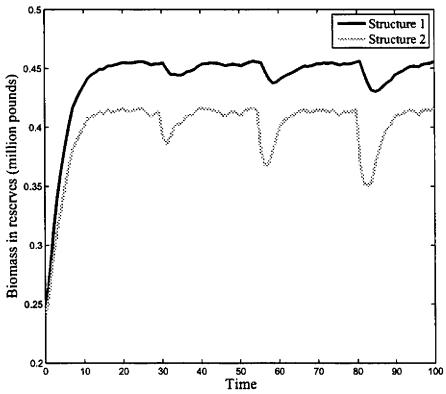
Since the population density is smoothed through fish migration, the difference in the total fish population between Structures 1 and 2 is not clear in Figure 4.3.2. However, the two network structures have different biological effects

Figure 4.4 **Biomass in fishing areas and reserves over time (negative shocks are realised only in the fishing areas)**

4.4.1 Fishing areas



4.4.2 Reserves



in the reserve and fishing ground, respectively. Figure 4.4 shows that the biomass in the fishing ground is higher and the impact of negative shocks on the harvested population is smaller in Structure 2. On the other hand, in the reserve, Structure 1 has a higher biomass and the reserve population is less impacted by the shocks. This is because the closer the linkage between the reserve and fishing ground, the greater the fish migration from the reserve to harvested areas. Furthermore, the greater the fish migration, the faster the population density among adjacent sites is smoothed. Consequently, the level of fish abundance between the reserve and fishing ground in Structure 2 is less differentiated than that in Structure 1. With a density dependent fish dispersal process, fish flows from high density to low density areas. Therefore, although a weaker connectivity between the reserve and harvested populations and a stronger linkage across the different reserves would maintain the reserve population better, there is a trade-off with the population density in the fishing ground and also with overall economic efficiency.

When negative shocks are realised in the whole environment. Figure 4.5 similarly illustrates the net profit from fishing and the total biomass under the two network structures, but negative shocks are now realised in both the

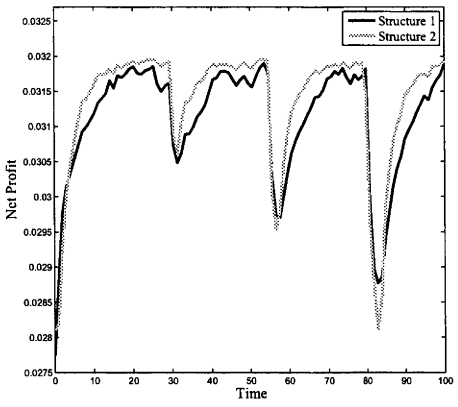
reserve and fishing ground. It is important to analyse different scenarios of negative shocks, because policy outcomes of marine reserves depend on the nature of large variations in fish populations (Grafton et al. 2006b; Costello & Polasky 2008).

The figure shows that, at the steady state, the net profit is greater when the reserve and harvested populations have a stronger connectivity. Also, due to the closer linkage between the reserve and harvested populations, there is less time for the trajectory of the net profit to recover, following the shocks. These results are similar to those in Figure 4.3. In contrast, the buffering effect immediately after the shocks is different from the previous case where negative shocks are only realised in the fishing ground. Figure 5 shows that, following the shocks, the net profit in Structure 2 is now temporally smaller than that in Structure 1, especially when the size of the shock is relatively large. This is because the closer connectivity in Structure 2 generates greater fish dispersal from the reserve to harvested areas and, in turn, this maintains a higher total profit than that in Structure 1. However, the negative shocks now occur in the whole environment and the population density falls in both the reserve and fishing ground simultaneously. The smoothing effect is consequently weaker and thus the buffering effect against the impact of negative shocks is also weaker than when the shocks are realised only in the fishing ground. As a result, the net profit in Structure 2 is temporally smaller than that in Structure 1.

When negative shocks occur in the whole environment, the biological effect in the reserve and fishing ground is also different from the previous case where the shocks are realised only in the fishing ground. Figure 4.6 illustrates this. Since negative shocks are now realised not only in the fishing ground but also in the reserve, the impact of the shocks on the reserve population is

Figure 4.5 **Net profit and biomass over time**
(negative shocks are realised in both the fishing areas and reserves)

4.5.1 Net profit



4.5.2 Biomass

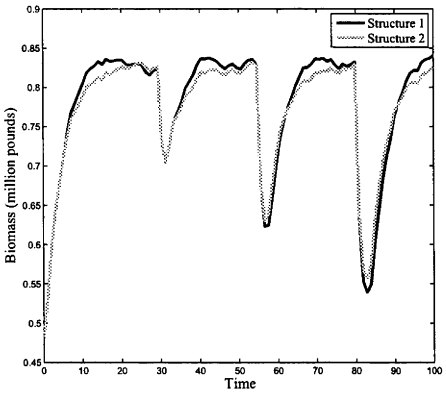
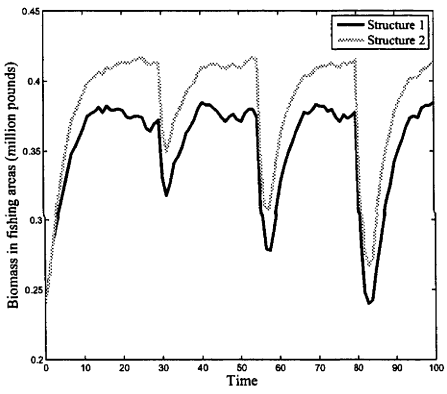
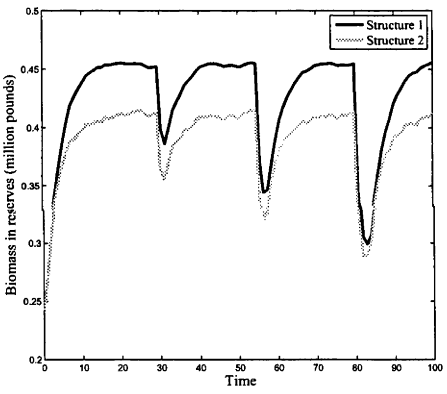


Figure 4.6 **Biomass in fishing areas and reserves over time**
(negative shocks are realised in both the fishing areas and reserves)

4.6.1 Fishing areas



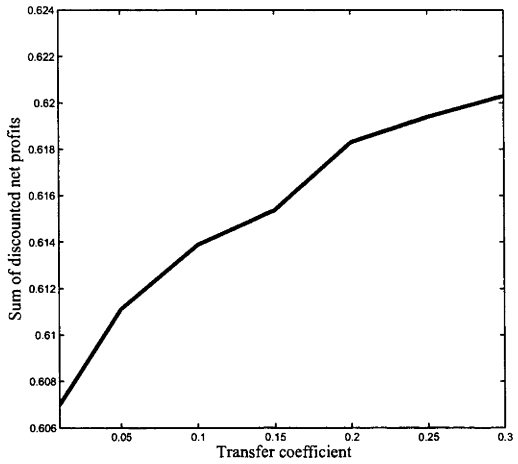
4.6.2 Reserves



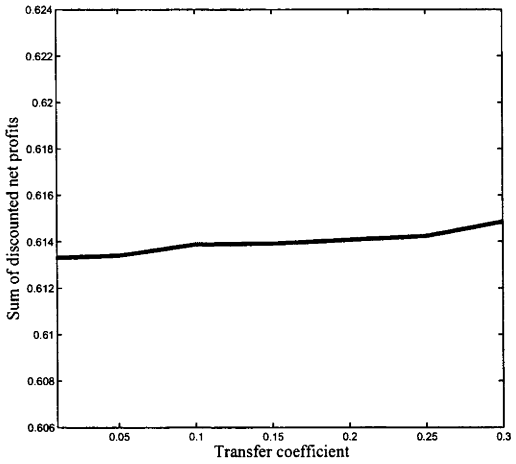
greater than the previous case. This is especially the case in Structure 1 where the reserve and harvested populations have a weaker connectivity. The lower fish migration from the reserve to the harvested areas in Structure 1, in other words the slower smoothing effect in the population density, mitigates the impact of negative shocks less. Furthermore, compared to the previous case, Structure 2 has a weaker buffering effect associated with the harvested population. This is because the smoothing effect is weaker when the shocks are realised in the whole environment, whereas Structure 2 mitigates the impact of negative shocks better when the shocks occur only in the fishing ground.

Figure 4.7 **Changes in the connectivity between adjacent sites (negative shocks are realised only in the fishing grounds)**

4.7.1 Changes in T_{12} and T_{34} in Structure 1



4.7.2 Changes in T_{23} and T_{41} in Structure 1

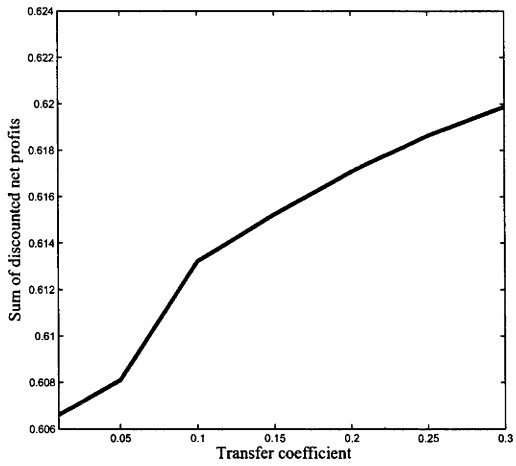


Connectivity. The results in the previous subsections show how the direct and indirect linkages between the reserve and harvested populations affect policy outcomes of marine reserves and how they respond to a large negative shock in fish populations. Depending on the network structure of reserves, the strength and nature of fish dispersal as well as the speed of smoothing the population density between adjacent sites are different. The role of direct/indirect linkages between adjacent sites is also emphasised in Figures 4.7 and 4.8. They illustrate how the value of the objective function changes in the transfer coefficient when negative shocks are realised only in the fishing ground and in the whole environment, respectively.

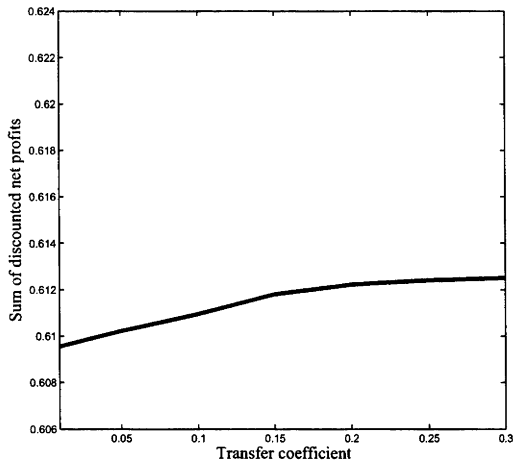
In Figures 4.7.1. and 4.8.1, we vary the value of the transfer coefficient between the reserve and fishing ground (T_{12} and T_{34}), while holding the linkage across the fishing grounds as well as the reserves constant. Alternatively, in Figures 4.7.2 and 4.8.2, the connectivity across the fishing grounds as well as the reserves is changed (T_{23} and T_{41}). Note that, here, only results in Structure 1 are presented, since we are interested in the difference between the changes in the direct (T_{12} and T_{34}) and indirect (T_{23} and T_{41}) linkages between the

Figure 4.8 **Changes in the connectivity between adjacent sites (negative shocks are realised in both the fishing grounds and reserves)**

4.8.1 Changes in T_{12} and T_{34} in Structure 1



4.8.2 Changes in T_{23} and T_{41} in Structure 1



reserve and harvested populations. It is clear from Figures 4.7 and 4.8 that the direct linkage between the reserve and harvested populations is a more important factor in determining the economic efficiency of marine reserves. As the value of the transfer coefficients (T_{12} and T_{34}) increases, fish dispersal from the reserve to harvested areas is enhanced, consequently increasing the economic return. However, a strong linkage between similar types of sites (T_{23} and T_{41}) is less likely to improve the economic efficiency, since it would not enhance fish dispersal between adjacent sites.

Overall, the results in this section suggest that a close connectivity that augments fish dispersal from the reserve to the harvested populations is important to maintain the economic efficiency of marine reserves. In other words, the distance from the reserves to the fishing grounds has to be close enough to ensure sufficient fish flows. Otherwise, the cost of reductions in fishing waters would be greater than the benefit from creating a reserve. Therefore, with a density dependent fish dispersal process, since fish flows from a high dense to low dense area, the direct linkage between the reserve and harvested populations dominates in determining the economic efficiency of marine reserves. Furthermore,

in a spatially homogeneous environment in the biological and economic characteristics, much dispersal benefit are not gained across the fishing grounds as well as the reserves. In the next section, we consider how the results vary in a heterogeneous environment.

Spatial heterogeneity of economic and biological parameters

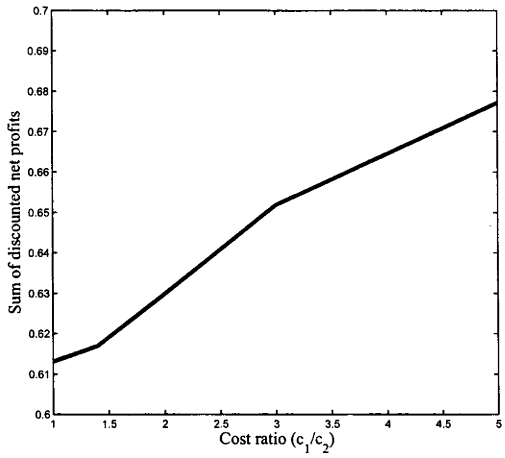
The policy outcomes of marine reserves are, in part, determined by the spatial heterogeneity of economic and biological parameters. The connectivity among adjacent sites, hence the strength and nature of fish dispersal, depends on site-specific characteristics. Figures 4.9 and 4.10 illustrate how the different scenarios of the spatial heterogeneity in the harvesting cost and intrinsic growth rate, respectively, affect economic returns in the fishery. Note that, hereafter, negative shocks are realised only in the fishing ground, but the key insights do not change if the shocks occur in the whole environment.

Harvesting costs. Harvesting costs are typically different across the fishing grounds. They vary depending on, for example, the distance from port to fishing grounds, local population density and site-specific ecological conditions. Clearly, if the harvesting cost in one fihsing ground is significantly highter than that in the other fishing ground, the optimal harvest in the later area is greater. Figure 4.9 illustrates how the sum of the discounted net profit changes in the cost ratio between the two fishing grounds in the two network structures. Here, the only heterogeneity is in the cost parameter, holding everything else constant. In Figure 4.9, the greater the value of the cost ratio, the larger the heterogeneity between the cost parameters c_i and c_j. In other words, when the cost ratio is one, the harvesting costs are the same across the two fishing grounds. The cost in a fishing ground becomes relatively greater than that in the other ground as the cost ratio increases.

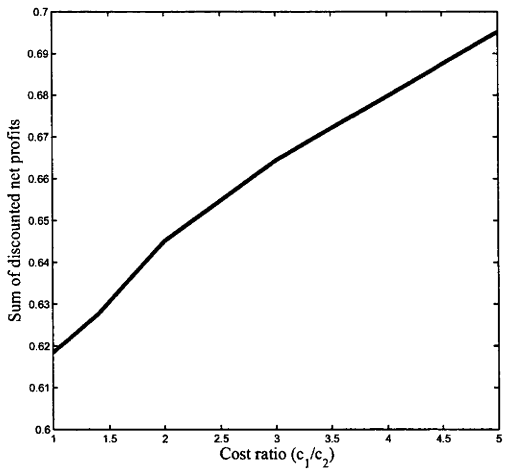
Figure 4.9 shows that the discounted net profit increases in the degree of het-

Figure 4.9 **Spatial heterogeneity of economic parameter (harvesting cost)**

4.9.1 Structure 1



4.9.2 Structure 2

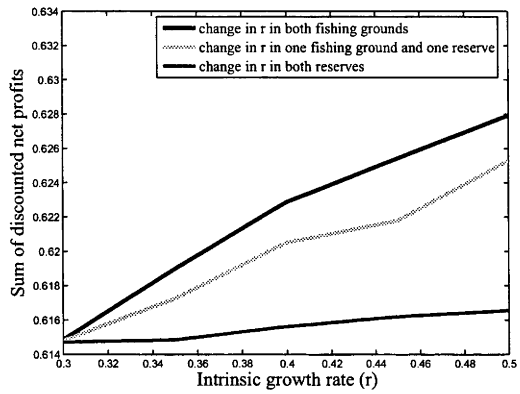


erogeneity in the cost parameter, holding the average harvesting cost constant ($(c_i + c_j)/2 = \bar{c}$). This is because, as the difference in the harvesting costs between the two fishing grounds increases, the optimal level of harvest, hence the population density becomes differentiated between the two fishing areas. With the differentiated population density over space, fish dispersal are enhanced not only from the reserve to harvested areas but also from one fishing ground to the other. The dispersal effect, consequently, increases the total economic return in the fishery. In other words, when the harvesting costs are constant over space, the optimal catch level, thus the population density, in each fishing ground is similar. In this case, fisheries do not obtain much dispersal benefit from the linkage across the fishing grounds.

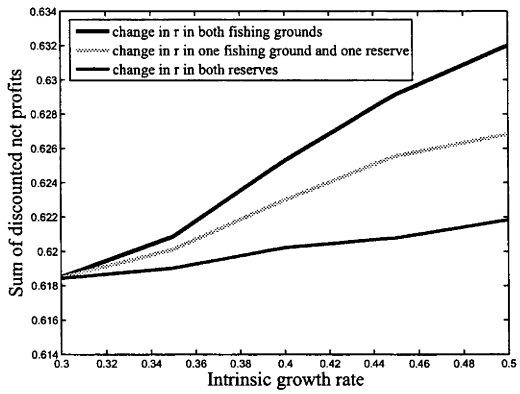
This result is important with respect to spatially explicit resource management. The result implies that, with a density dependent fish dispersal process, the profitability of a fishery is more likely to be improved by imposing a spatially explicit catch/effort limit than a constant limit over space. This is not only because the spatially explicit catch/effort limit is compatible with the site-specific conditions but also because it enhances the dispersal benefit. In other words, a trade-off in the decision to harvest today is not only with a decision

Figure 4.10 Spatial heterogeneity of biological parameter (intrinsic growth rate)

4.10.1 Structure 1



4.10.2 Structure 2



to leave the fish for future generations but also with a decision to leave the fish for the next period to enhance the dispersal benefit through smoothing the population density over space. Also, in an extreme case where the harvesting costs across the fishing grounds are significantly differentiated, the optimal level of harvest at one of the sites is a corner solution, $h^i = 0$, so that it is optimal to close the fishing ground (Sanchirico et al 2006). Moreover, if the harvesting costs are further differentiated from this point, because the fishing ground with the higher harvesting cost is now closed, the total harvesting cost further decreases which, in turn, increases total economic returns.

Intrinsic growth rates. The growth rate of fish is another important factor in determining policy outcomes of marine reserves and the spatial heterogeneity in the growth rate influences the connectivity between adjacent sites. Previous studies, for example, show that, as the growth rate increases either in the whole environment or in the reserve, the optimal size of reserves decreases (Grafton et al. 2005) and the parameter region for a win-win situation, where both the economic and biological conditions are improved, becomes restrictive (Sanchirico & Wilen 2001 and 2002). This is because the higher the intrinsic growth rate, the greater the resilience of the biomass and the smaller the reserve is necessary to maintain populations.

To see how the spatial heterogeneity in the intrinsic growth rate affects policy outcomes, we vary the value of the growth rate in the reserve and fishing ground, respectively, in Figure 4.10. The figure shows that fish growth in the fishing ground is more important to determine the economic efficiency of marine reserves than in the reserve. This is because, the higher the growth rate the greater the resilience of the harvested population, which is more profitable to harvest in the area where growth rates are relatively high. This result is consistent with previous studies, including Sanchirico et al. (2006). They show that unless the dispersal benefit from the reserve to harvested populations is sufficient to outweigh the returns from harvesting in the site with high growth rates, it is optimal to close the area where the growth rate is relatively low. In other words, whether which area to be closed for fishing depends on the relative benfits of fish dispersal and production. This result is also relevant to the buffering effect of marine reserves, since fishing grounds are exposed to a higher risk of environmental degradation than reserves due to human activities. Opening a site with higher growth rates enhances the resilience of the system against a negative shock.

Concluding remarks

To address issues on the connectivity of marine reserves, we develop a spatial bioeconomic model, which incorporates a simple network structure of reserves. Then we solve and simulate the model using a feedback approximation method. We find that, if the connectivity between the reserve and harvested populations is weak and reserves are close together, then it maintains the reserve population better; however, there is a trade-off with the spatial distribution of fish populations and also with economic efficiency in the fishery. We also show that fish dispersal from the reserve to harvested areas are enhanced in

a heterogeneous environment. This is because, with heterogeneous ecological and economic conditions, the optimal control of resource use is not constant over space. With a spatially explicit harvest/effort control, population density across adjacent sites is also not uniform which, in turn, enhances the dispersal effect from the reserve to harvested areas. Therefore, a spatially explicit control outweighs a non-spatial one not only because it is compatible with site-specific conditions but also because it enhances the dispersal effect.

This paper employs a density dependent fish dispersal process, which is a common specification in the literature, but the biological dispersal process is typically subject to different factors, such as, sea temperature, currents and natal habitat. Other spatial bioeconomic models employ, for example, unidirectional and life-stage dependent dispersal processes (Brown & Roughgarden 1997; Sanchirico & Wilen 1999) However, we note that the main insights in this paper would be applicable in natural resource management as long as a similar kind of smoothing effect is in presence in neighbouring populations. For future research, it would be worth analysing trade-offs across the connectivity, biological and economic efficiency as well as the resilience of marine reserves while incorporating a model with multiple nodes and clusters of the reserve and harvested populations.

Appendix

Matlab code

```
%%%% conn.m
%%%%
%%%% This program solves a dynamic bioeconomic model
%%%% by using a feedback approximation method.
%%%% See Sirakaya et al (2006) in CE
%%%%
%%%% To run this program Genetic Algorithm and
%%%% Direct Search Toolbox is required.
%%%%

clear all
close all
clc

options =
gaoptimset('PopulationSize',50,'PopInitRange',[-100;100],
'MutationFcn',{@mutationgaussian,1,0.7},
'Generations',1000, 'StallGenLimit', inf,'StallTimeLimit', inf);

[x fval] = ga(@fish13_r_3_t1,38,[],[],[],[],[],[],[],options);

beta = 0.95;
delta = 1.23;
p = .07;
c = .03;
r1 = .2985;
r2 = .2985;
m = .1;
K = 0.9631;
size = 0.5;
k1 = size/2;
k2 = (1-size)/2;
k3 = (1-size)/2;
K1 = K*k1;
K2 = K*k2;
K3 = K*k3;
K4 = K-K1-K2-K3;
load epidemic
```

```
time = 100;

% DEFINE VARIABLES
x1t = zeros(time+1,1);
x2t = zeros(time+1,1);
x3t = zeros(time+1,1);
x4t = zeros(time+1,1);
xt = zeros(time+1,1);
h1t = zeros(time,1);
h3t = zeros(time,1);
ht = zeros(time,1);
nrt = zeros(time,1);
t1 = zeros(time,1);
t2 = zeros(time,1);
t3 = zeros(time,1);
t4 = zeros(time,1);

x10 = .5;
x20 = .5;
x30 = .5;
x40 = .5;
x1t(1,1) = x10*K1;
x2t(1,1) = x20*K2;
x3t(1,1) = x30*K3;
x4t(1,1) = x40*K4;

w = x;

for i = 1:time

xt(i) = x1t(i) + x2t(i) + x3t(i) + x4t(i);

h1t(i) = min(max(0 + (K1-0)*
(1/(1+exp(-(w(1)*1/(1+exp(-(w(2)*x1t(i)+w(3))))
+w(4)*1/(1+exp(-(w(5)*x2t(i)+w(6))))
+w(7)*1/(1+exp(-(w(8)*x3t(i)+w(9))))
+w(10)*1/(1+exp(-(w(11)*x4t(i)+w(12))))
+w(13)*1/(1+exp(-(w(14)*z(i)+w(15))))
+w(16)*1/(1+exp(-(w(17)*s1(i)+w(18))))+w(19))))),0),K1);

h3t(i) =min(max(0 + (K3-0)*
(1/(1+exp(-(w(20)*1/(1+exp(-(w(21)*x1t(i)+w(22))))
+w(23)*1/(1+exp(-(w(24)*x2t(i)+w(25))))
+w(26)*1/(1+exp(-(w(27)*x3t(i)+w(28))))
+w(29)*1/(1+exp(-(w(30)*x4t(i)+w(31))))
```

```
+w(32)*1/(1+exp(-(w(33)*z(i)+w(34))))
+w(35)*1/(1+exp(-(w(36)*s1(i)+w(37))))+w(38))))),0),K3);

ht(i) = h1t(i) + h3t(i);
nrt(i) = p*ht(i)^(1-1/delta)- c/x1t(i)*h1t(i) - c/x3t(i)*h3t(i);
x1t(i+1) = x1t(i) + r1*z(i)*x1t(i)*(1-x1t(i)/K1) + m*K1*(x2t(i)/K2 -
x1t(i)/K1) + m*K1*(x4t(i)/K4 - x1t(i)/K1)- s1(i)*x1t(i) - h1t(i);
x2t(i+1) = x2t(i) + r1*z(i)*x2t(i)*(1-x2t(i)/K2) - m*K1*(x2t(i)/K2 -
x1t(i)/K1) + m*K2*(x3t(i)/K3 - x2t(i)/K2);
x3t(i+1) = x3t(i) + r2*z(i)*x3t(i)*(1-x3t(i)/K3) - m*K2*(x3t(i)/K3 -
x2t(i)/K2) + m*K3*(x4t(i)/K4 - x3t(i)/K3) - s1(i)*x3t(i) - h3t(i);
x4t(i+1) = x4t(i) + r2*z(i)*x4t(i)*(1-x4t(i)/K4) - m*K3*(x4t(i)/K4 -
x3t(i)/K3) - m*K1*(x4t(i)/K4 - x1t(i)/K1);
t1(i) = m*K1*(x2t(i)/K2 - x1t(i)/K1);
t2(i) = m*K2*(x3t(i)/K3 - x2t(i)/K2);
t3(i) = m*K3*(x4t(i)/K4 - x3t(i)/K3);
t4(i) = m*K1*(x4t(i)/K4 - x1t(i)/K1);

end
```

Endnote

[1] See Appendix for Matlab code.

[2] For the details of the theory of neural networks, see for example Hertz et al. (1991).

[3] For the detailed discussion on genetic algorithm, see for example Holland (1992).

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